

RESEARCH ARTICLE

Socio-Economic Determinants of Safe Pesticide Use among Vegetable Growers in Jaipur District: A Multivariate and Machine Learning Analysis

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ABSTRACT

Vegetable production is a cornerstone of Rajasthan's agricultural economy, particularly in Jaipur District, but faces challenges from biotic stresses. Safe and informed pesticide use is critical to mitigate these losses while minimizing health and environmental risks. Understanding the socio-economic factors that influence pesticide utilization behavior (PUB) among vegetable growers is essential for promoting sustainable practices in this region. The study was conducted in Bassi and Amber tehsils of Jaipur District, selected for their prominence in vegetable cultivation. Four villages per tehsil were randomly selected, and 15 vegetable growers per village were chosen, yielding 120 respondents. Correlation analysis examined relationships between socio-economic factors and PUBs. Structural equation modeling with maximum likelihood estimation and robust corrections for ordinal data modeled a latent construct of PUB predicted by socio-economic variables. Decision tree analysis validated key predictors. This study underscores the critical role of socio-economic factors, particularly crop diversity, in shaping pesticide use behaviors. By integrating multivariate and machine learning approaches, it provides actionable insights for policymakers and extension services to design targeted interventions, enhancing sustainable vegetable production and reducing health and environmental risks in Jaipur District and similar regions.

Key words: Decision tree analysis, multivariate analysis, pesticide utilization behavior, socio-economic determinants, structural equation modeling, vegetable growers

INTRODUCTION

Vegetable farming in India relies heavily on pesticides to protect crops from pests and diseases, ensuring consistent yields and economic viability for growers. However, the misuse of these chemicals often leads to severe consequences, including health issues among farmers, soil and water contamination, and harm to non-target species such as pollinators (Aktar *et al.*, 2009). Rajasthan, a state with a significant agricultural base, faces these challenges

acutely, particularly in districts like Jaipur, where vegetable cultivation is a cornerstone of the local economy. Despite the known risks, many farmers in this region continue to handle pesticides unsafely due to a lack of awareness, limited resources, or inadequate access to training programs (Kumar *et al.*, 2017). Socio-economic factors, including education, income, and land ownership, play a pivotal role in shaping these safety practices, as they often determine a farmer's ability to adopt protective measures or access extension services (Banerjee *et al.*, 2014).

While previous studies have explored pesticide use patterns in India, the specific dynamics of safe pesticide handling among Jaipur's vegetable

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growers remain underexplored. Existing research often focuses on broader national trends or other regions, overlooking the unique socio-economic diversity of Rajasthan's farming communities (Sharma *et al.*, 2015). For instance, education levels can influence a farmer's understanding of pesticide labels, while income and land holding size may affect their ability to purchase safety equipment or adopt integrated pest management (IPM) practices (Singh and Gupta, 2018). Moreover, traditional statistical methods alone may not fully capture the complex interplay of these factors, necessitating advanced approaches like multivariate regression and machine learning to uncover key predictors and behavioral patterns (Jha *et al.*, 2022). Jaipur's diverse farming population, spanning various castes, income levels, and land holdings, offers a compelling context to investigate these relationships and address gaps in safe pesticide use.

This study holds significant potential to advance agricultural safety in Rajasthan. By identifying the socio-economic drivers of safe pesticide practices, it aims to provide actionable insights for policymakers and extension services to design targeted interventions. The use of multivariate regression allows for a nuanced understanding of which factors most strongly predict safe behaviors, while decision tree analysis helps classify farmers into distinct safety behavior groups, facilitating tailored training programs (Fan *et al.*, 2015). Addressing these issues is critical not only for reducing health and environmental risks but also for promoting sustainable farming practices that align with India's broader agricultural development goals (Pretty and Bharucha, 2015).

To achieve these goals, this research pursues the following objectives: (1) to investigate the relationships between socio-economic factors, such as education, income, and land holding, and safe pesticide use behaviors among vegetable growers in Jaipur District; (2) to identify key predictors of safe pesticide use through Structural equation modeling (SEM); (3) to classify farmers by their safety behavior levels using machine learning techniques, specifically decision trees; and (4) to provide evidence-based recommendations for targeted training programs to enhance pesticide safety. By combining multivariate and machine

learning approaches, this study seeks to offer a comprehensive understanding of safe pesticide use in Jaipur, contributing to improved farmer well-being and environmental sustainability in Rajasthan's vegetable farming sector.

Rationale

Socio-economic factors influence safe pesticide use, but their impact in Rajasthan's vegetable farming sector is underexplored. Jaipur's diverse farming community provides a unique context to examine these dynamics using multivariate and machine learning approaches. This study identifies key drivers of safe practices, offering insights for extension services to mitigate health and environmental risks.

RESEARCH METHODOLOGY

This section outlines the methods and procedures used to investigate pesticide use practices and safety behaviors among vegetable growers in Jaipur District, Rajasthan. It covers the study locale, sampling, research tools, data collection, and statistical analyses.

Locale of the Study

The study was conducted in Jaipur District, selected for its highest vegetable cultivation area (39,071 ha) and production (166,472 MT) in Rajasthan (Directorate of Horticulture, 2018–19), due minimal prior pesticide uses studies, enabling efficient data collection.

Sampling Procedure

Bassi and Amber tehsils were selected based on high vegetable cultivation area, using Revenue Department data. Four villages per tehsil, that is, Achrol, Chonp, Kacherawala, and Khurad from the Amber tehsil; and Deogaon, Kashipura, Khatepura, and Moondli villages from Amber tehsil were randomly selected from Census 2011 data. Fifteen vegetable growers per village were randomly selected using Patwari lists, yielding a sample of 120 farmers.

Development of Research Tools

An interview schedule measured independent variables (age, caste, occupation, education, farming experience, income, land holding, use of farming apps, and family size) and pesticide utilization behaviors (PUB) related variables (use rate, information sources, container disposal, pollinator protection, pest management, spraying decisions, and frequency). Scales from Trivedi (1963), Kuppuswamy and Udai Pareekh (2019), and Muhammad *et al.* (2019) were used with expert modifications. Qualitative variables were categorized (e.g., age: Young ≤ 36 years; education: Illiterate to above graduate) and scored as per past practices.

Collection of Data

Data were collected through direct interviews using a structured schedule, administered to 120 farmers across eight villages, capturing socio-personal and pesticide use behaviors comprehensively.

Analysis of Data

Data were analyzed in the Statistical Package for the Social Sciences and JMP Pro, using correlation analysis to assess relationships, SEM to identify predictors of PUB, and decision trees to classify farmers by behavior levels.

Statistical Measures

The analyses supported the study's objectives. The correlation analysis used Pearson's correlations to examine relationships between socio-economic factors (e.g., education, income, and farming experience) and PUBs, with r and P -values ($P < 0.05$). SEM modeled a latent "pesticide utilization behavior" construct predicted by age, education, occupation, vegetable farming experience, farming experience, number of crops, and income, using maximum likelihood with robust corrections for ordinal data. Fit was assessed through χ^2 , comparative fit index (CFI) (>0.90), root mean square error of approximation (RMSEA) (<0.08), with path coefficients at $P < 0.05$. Decision trees used CHAID to classify high/low behavior

groups, with accuracy. Small sample size ($n = 120$) was noted as a limitation.

RESULTS AND DISCUSSION

Assess Relationships between Socio-Economic Variables and PUBs

A notable challenge in this analysis was the high intercorrelations among the independent variables, which likely contributed to multicollinearity issues. For example, age was strongly correlated with experience of vegetable farming ($r = 0.884$, $P < 0.01$) and farming experience ($r = 0.827$, $P < 0.01$), while education level and occupation were also highly correlated ($r = 0.762$, $P < 0.01$). Similarly, annual income showed strong correlations with occupation ($r = 0.834$, $P < 0.01$) and education level ($r = 0.708$, $P < 0.01$). These interdependencies suggest that socio-economic factors are deeply interconnected among Jaipur's vegetable growers, reflecting the complex socio-economic fabric of the region (Singh and Gupta, 2018). However, this multicollinearity undermined the utility of a standard multiple regression model, which exhibited low explanatory power and non-significant coefficients for most predictors. Consequently, SEM was adopted to capture the complex relationships and latent constructs better, as discussed in the next section. This lack of significant correlations between PUB and most socio-economic factors contrasts with some prior studies, which often report that education and income positively influence safe pesticide use (Damalas and Hashemi, 2010). The absence of such relationships in this study may reflect the unique context of Jaipur District, where awareness campaigns or local regulations might have normalized certain safety behaviors across socio-economic groups, as evidenced by the high adoption of protective equipment (76.7% "Always," as noted in your earlier data). Alternatively, the small sample size ($n = 120$) may have limited the statistical power to detect weaker relationships, a common issue in agricultural studies with small samples (Kumari and Chander, 2020).

Predict Safe Pesticide use from Socio-Economic Factors

To identify key predictors of safe pesticide use, an SEM was employed with PUB as a latent

Table 1: Descriptive statistics of variables

Parameters	<i>n</i>	Minimum	Maximum	Mean	Standard deviation
Age	120	29.00	55.00	41.6750	6.93810
Education level	120	1.00	8.00	4.0250	2.28794
Occupation	120	1.00	4.00	2.2667	0.99354
Experience of vegetable farming	120	3.00	15.00	8.3000	3.49694
Farming experience (in years)	120	1.00	3.00	2.0000	0.72181
Number of crop grown in the season	120	2.00	6.00	3.7333	1.00196
Annual income	120	100000.0	1000000.0	363333.33	220935.11

variable influenced by the observed socio-economic variables, that is, age, education level, occupation, experience of vegetable farming, farming experience, number of crops grown, and annual income [Tables 1-6]. Descriptive statistics [Table 1] highlighted the diversity of the sample, with a mean age of 41.68 years (standard deviation [SD] = 6.94), a mean annual income of 363,333.33 INR (SD = 220,935.11), and an average of 3.73 crops grown per season (SD = 1.00), reflecting the varied socio-economic profiles of the 120 vegetable growers in Jaipur District.

The SEM model fit indices [Table 2] indicated a poor fit, with a Chi-square value of 777.287 (df = 20, $P < 9.34e^{-152}$), a CFI of 0.003, and a RMSEA of 0.562 (90% confidence interval: 0.528–0.596). These metrics suggest that the model does not adequately represent the data, as a well-fitting model typically requires a CFI > 0.90 and RMSEA < 0.08 (Kline, 2015). The poor fit can likely be attributed to the small sample size ($n = 120$) and high multicollinearity among predictors, which can destabilize SEM estimates (Bollen, 1989). In addition, PUB was measured as a single latent variable with limited indicators, which may not fully capture the multidimensional nature of PUBs, such as frequency of application, protective equipment uses, or disposal practices.

Despite these limitations, the SEM provided some insights into the relationships between variables. The estimated means [Table 3] confirmed the descriptive statistics, with all constants being statistically significant ($P < 0.0001$). Variance estimates [Table 5] were significant for all observed variables ($P < 0.0001$, except PUB at $P = 0.0035$), with age showing the highest variance (47.736, $P < 0.0001$) and PUB a variance of 2.169 ($P = 0.0035$). Covariance estimates [Table 6] revealed that only the number of crops grown had

Table 2: Summary of model fit indices for the structural equation model

Metric	Value	Metric	Value
Sample size	120	Chi-square	777.287
Rows with missing	0	Degrees of freedom	20
–2 Log likelihood	3570.821	Prob>Chi-Sq	9.34e ⁻¹⁵²
Iterations	151	CFI	0.003
Number of parameters	24	RMSEA	0.562
AICc	3631.453	RMSEA lower 90%	0.528
BIC	3685.721	RMSEA upper 90%	0.596

CFI: Comparative fit index, RMSEA: Root mean square error of approximation

a significant covariance with PUB (cov = 0.459, $P = 0.0161$), corroborating the correlation analysis. Other variables, such as education (cov = –0.563, $P = 0.3393$) and annual income (cov = –0.094, $P = 0.4292$), showed no significant covariance with PUB.

The significant relationship between the number of crops grown and PUB aligns with the notion that diversified cropping systems increase reliance on pesticides, a trend observed in other Indian agricultural contexts (Sharma *et al.*, 2015). However, the lack of significant effects from education and income contrasts with studies suggesting that higher education enhances safety practices through better label comprehension and risk awareness (Damalas and Hashemi, 2010). This discrepancy may stem from overconfidence among educated farmers, as noted in prior research (Jallow *et al.*, 2017), or the effectiveness of local awareness campaigns in Jaipur, which may have standardized safety behaviors across socio-economic groups. The poor model fit underscores the need for future research to refine the SEM by including additional indicators for PUB (e.g., specific safety practices like disposal methods or pollinator protection) and addressing multicollinearity, possibly by combining correlated variables such as experience of vegetable farming and total farming experience.

Table 3: Estimated means and intercepts

Parameter	Estimate	Standard error	Wald Z	Prob > Z
Constant→age	41.675	0.631	66.076	<0.0001*
Constant→pesticide utilization behaviors	25.367	0.159	158.797	<0.0001*
Constant→education	4.025	0.208	19.352	<0.0001*
Constant→occupation	2.267	0.090	25.096	<0.0001*
Constant→experience of vegetable Farming	8.3	0.318	26.109	<0.0001*
Constant→farming experience	2	0.066	30.480	<0.0001*
Constant→No. of crops grown	3.733	0.091	40.988	<0.0001*
Constant→annual income	2.017	0.051	39.275	<0.0001*

Asterisks (*) indicate statistical significance at $P < 0.05$

Table 4: Latent variable loadings

Parameter	Estimate	Standard error	Wald Z	Prob > Z
Latent1→pesticide utilization behaviors	1	-	-	-

Standard error, Wald Z, and P -value are not applicable (denoted by “-”) as the loading is fixed at 1

The diagram (Figure 1) represents a structural equation model with a latent variable, Latent1, influencing the observed variable PUB, alongside several other observed variables (Age, Education, Occupation, Exp, Farming experience, No. of crop grown, and Annual Income) that covary with PUB. The results from the diagram and prior data can be summarized as follows:

Cluster Farmers based on Pesticide use and Safety Behaviors

The third objective was to classify farmers based on their pesticide utilization and safety behaviors using a CHAID decision tree, with utilization behavior as the dichotomous dependent variable (Low vs. high pesticide utilization behavior) and socio-economic factors as predictors [Tables 7 and 8, Figure 2]. The risk table [Table 7] reported a resubstitution error of 0.383 (SE = 0.044), indicating that the model misclassifies 38.3% of cases in the training data, and a cross-validation error of 0.483 (SE = 0.046), suggesting moderate overfitting as the error rate increases on unseen data. Compared to previous iterations (cross-validation errors of 0.425, 0.450, and 0.442), the current cross-validation error of 0.483 reflects increased variability, possibly due to adjustments in CHAID settings (e.g., node sizes and random seed) or fold differences in cross-validation. The classification [Table 8] showed an overall accuracy of 61.7%, with 39 out of 69 cases

correctly classified as “Low pesticide utilization behavior” (56.5% accuracy) and 35 out of 51 cases correctly classified as “High pesticide utilization behavior” (68.6% accuracy). The model is more effective at predicting “High” utilization behavior, but its overall accuracy is only slightly better than the baseline accuracy of 57.5% (if all cases were predicted as “Low,” the majority class with 69/120 cases). This marginal improvement suggests that the predictors may not strongly differentiate between low and high utilization behaviors, consistent with the weak correlations observed in Table 9.

Figure 2, the decision tree, identified the number of crops grown as the primary predictor (Zscore: Number of crops grown in the season), splitting farmers at a Zscore of 0.0731900 into two nodes: Node 6 (Zscore < 0.0731900, $n = 55$), where 70.9% exhibited low utilization behavior, and Node 2 (Zscore > 0.0731900, $n = 65$), where 53.8% exhibited high utilization behavior (ADJ. $P = 0.025$, Chi-square = 7.471, $df = 1$). This finding reinforces the significant role of crop diversity in shaping pesticide utilization patterns, as also seen in the correlation and SEM analyses.

The moderate accuracy of the decision tree (61.7%) and its limitations can be attributed to several factors. First, the Z-score transformation of nominal (e.g., education and occupation) and ordinal (e.g., farming experience) variables likely forced CHAID to treat them as continuous, reducing its ability to perform chi-square-based splits optimal for categorical data (Fan *et al.*, 2015). Reverting to raw categorical values could improve the model’s performance. Second, the small sample size ($n = 120$) and restrictive CHAID settings (e.g., high minimum node sizes and shallow tree depth) may

Table 5: Variance estimates for observed and latent variables

Parameter	Estimate	Standard error	Wald Z	Prob > Z
Age↔age	47.736	6.162	7.745	<0.0001*
Pesticide Utilization Behaviors↔pesticide Utilization Behaviors	2.169	0.744	2.916	0.0035*
Education↔education	5.191	0.670	7.746	<0.0001*
Occupation↔occupation	0.979	0.126	7.746	<0.0001*
Experience of vegetable farming↔experience of vegetable farming	12.127	1.566	7.746	<0.0001*
Farming experience↔farming experience	0.517	0.067	7.746	<0.0001*
No. of Crops Grown↔No. of Crops Grown	0.996	0.129	7.746	<0.0001*
Annual income↔annual income	0.316	0.041	7.746	<0.0001*
Latent1↔latent1	0.892	0.000	-	-

Asterisks (*) indicate statistical significance at $P < 0.05$. The variance for Latent1 has a standard error of 0, making Wald Z and P -value inapplicable

Table 6: Covariance estimates between variables

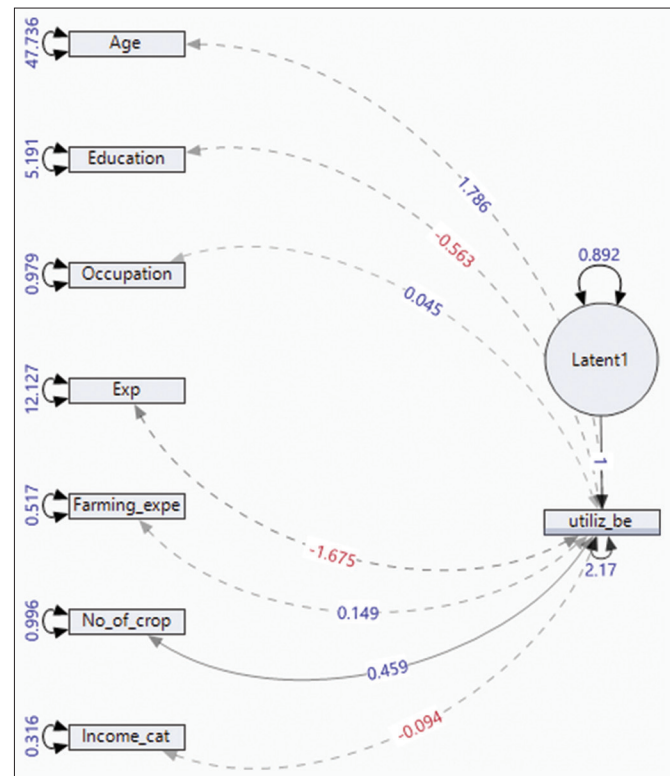
Parameter	Estimate	Standard error	Wald Z	Prob > Z
Age↔pesticide utilization behaviors	1.786	2.406	0.742	0.4579
Education↔pesticide utilization behaviors	-0.563	0.590	-0.955	0.3393
Occupation↔pesticide utilization behaviors	0.045	0.305	0.148	0.8826
Experience of vegetable farming↔pesticide utilization behaviors	-1.675	1.563	-1.071	0.2840
Farming experience↔pesticide utilization behaviors	0.149	0.271	0.551	0.5819
No. of crops grown↔pesticide utilization behaviors	0.459	0.191	2.407	0.0161*
Annual income↔pesticide utilization behaviors	-0.094	0.119	-0.791	0.4292

Asterisks (*) indicate statistical significance at $P < 0.05$

Table 7: Risk table

Method	Estimate	Standard error
Resubstitution	0.383	0.044
Cross-validation	0.483	0.046

have constrained tree growth, resulting in a simple model with limited branching. Third, the lack of detailed outputs, such as gain summaries or variable importance, due to undefined profits and target categories, limits the interpretability of node-specific insights, hindering the ability to tailor interventions. Despite these challenges, the decision tree provides a practical framework for classifying farmers, supporting the study's objective to inform targeted training programs. Farmers in Node 2 (high utilization behavior) may benefit from training focused on IPM to reduce pesticide reliance, while those in Node 6 (low utilization behavior) could serve as models for peer learning, similar to the "early adopters" described in diffusion of innovation theory (Rogers, 2003). These findings highlight the need for extension services to address specific safety gaps, such as improper disposal practices and lack of pollinator protection, which pose risks to both the environment and agricultural productivity (Garibaldi *et al.*, 2013; Mishra *et al.*, 2018).

**Figure 1:** Path diagram

Implications for Targeted Training Programs

The combined findings from the correlation, SEM, and decision tree analyses offer actionable insights

Table 8: Classification table

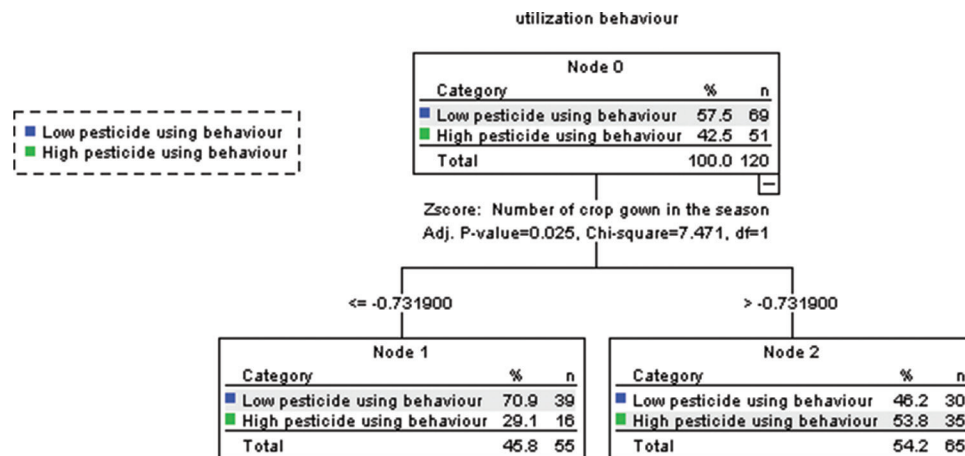
Observed	Predicted		
	Low pesticide utilization behavior	High pesticide utilization behavior	Percent correct
Low pesticide utilization behavior	39	30	56.5
High pesticide utilization behavior	16	35	68.6
Overall percentage	45.8	54.2	61.7

Dependent variable: Pesticide utilization behavior, Growing method: CHAID

Table 9: Correlations between socio-economic factors and safety behaviors

Variables	Age	EL	Occ	EVF	FE	NCG	AI	PUB
Age	1.000	-0.725**	-0.672**	0.884**	0.827**	-0.287**	-0.592**	0.057
EL	-0.725**	1.000	0.762**	-0.696**	-0.717**	0.373**	0.708**	-0.081
Occ	-0.672**	0.762**	1.000	-0.582**	-0.609**	0.570**	0.834**	-0.014
EVF	0.884**	-0.696**	-0.582**	1.000	0.919**	-0.320**	-0.570**	0.000
FE	0.827**	-0.717**	-0.609**	0.919**	1.000	-0.349**	-0.624**	0.021
NCG	-0.287**	0.373**	0.570**	-0.320**	-0.349**	1.000	0.489**	0.194*
AI	-0.592**	0.708**	0.834**	-0.570**	-0.624**	0.489**	1.000	-0.025
PUB	0.057	-0.081	-0.014	0.000	0.021	0.194*	-0.025	1.000

EL: Education level, Occ: Occupation, EVF: Experience of vegetable farming, FE: Farming experience (years), NCG: No. of crops grown, AI: Annual income, PUB: Pesticide utilization behaviors. **Correlation is significant at the 0.01 level (two-tailed) ($n=120$)

**Figure 2:** Decision tree for predicting safe pesticide use

for designing targeted training programs, fulfilling the study's fourth objective. The consistent significance of the number of crops grown across all analyses suggests that farmers with greater crop diversity are more likely to exhibit high PUBs, potentially increasing health and environmental risks. Extension programs should prioritize these farmers for training on IPM strategies, which can reduce pesticide dependency while maintaining crop yields (Pretty and Bharucha, 2015). In addition, the decision tree's classification of farmers into low and high utilization groups enables tailored interventions. For instance, farmers with high utilization behaviors (Node 2) may require education on safe disposal methods (e.g., recycling

containers) and pollinator-friendly practices (e.g., evening spraying), addressing critical gaps identified in prior research (Mishra *et al.*, 2018; Garibaldi *et al.*, 2013).

The lack of significant effects from education and income on PUB suggests that current awareness campaigns in Jaipur may have leveled safety practices across socio-economic groups, a positive outcome that can be built on. However, the puzzling lower adoption of protective equipment among graduates and large farmers, as noted in your earlier data, warrants further investigation. Training programs could address potential overconfidence among educated farmers by emphasizing risk awareness and practical safety demonstrations

(Jallow *et al.*, 2017). Future research should also address the methodological limitations identified, such as increasing the sample size, refining the SEM model with additional PUB indicators, and optimizing CHAID settings to enhance model performance and generalizability.

CONCLUSION

This study aimed to explore the socio-economic determinants of safe pesticide use among vegetable growers in Jaipur District, Rajasthan, using a combination of multivariate and machine learning approaches. The research pursued four objectives: (1) to investigate relationships between socio-economic factors (e.g., education, income, land holding) and safe pesticide use behaviors, (2) to identify key predictors of safe pesticide use through multivariate regression and SEM, (3) to classify farmers by safety behavior levels using machine learning (decision trees), and (4) to inform targeted training programs for enhancing pesticide safety.

The correlation analysis revealed that PUB had a weak positive correlation with the number of crops grown ($r = 0.194$, $P < 0.05$), suggesting that farmers with greater crop diversity tend to rely more on pesticides, likely due to increased pest pressure (Sharma *et al.*, 2015). However, PUB showed no significant correlations with other socio-economic variables, such as education, income, or age, possibly due to the uniform impact of local awareness campaigns in Jaipur District or the small sample size ($n = 120$) limiting statistical power (Kumari and Chander, 2020). High intercorrelations among predictors (e.g., age and farming experience, $r = 0.827$, $P < 0.01$) indicated multicollinearity, which undermined the effectiveness of standard regression models, prompting the use of SEM.

The SEM analysis further confirmed the significant role of the number of crops grown (cov = 0.459, $P = 0.0161$) in predicting PUB, but other socio-economic factors, including education and income, showed no significant effects. However, the model exhibited poor fit (CFI = 0.003, RMSEA = 0.562), likely due to the small sample size and multicollinearity among predictors (Kline, 2015). This suggests that while the number of crops grown is a key driver of pesticide utilization, the model requires refinement, such as including additional

indicators for PUB (e.g., specific safety practices) or addressing multicollinearity by combining correlated variables.

Using a CHAID decision tree, farmers were classified into low and high PUB groups based on the number of crops grown as the primary predictor (ADJ. $P = 0.025$, Chi-square = 7.471, $df = 1$). The tree achieved an overall accuracy of 61.7%, with better performance in predicting high utilization behavior (68.6%) than low (56.5%). However, the cross-validation error (0.483) indicated moderate overfitting, and the model's accuracy was only slightly better than the baseline (57.5%), reflecting limitations such as the Z-score transformation of categorical variables, small sample size, and restrictive CHAID settings (Fan *et al.*, 2015). Despite these challenges, the decision tree provided a practical framework for identifying farmer groups for targeted interventions.

This study provides valuable insights into the socio-economic determinants of safe pesticide use among vegetable growers in Jaipur District, highlighting the significant influence of crop diversity on PUBs. The consistent finding across correlation, SEM, and decision tree analyses that the number of crops grown is a key predictor underscores the need for tailored agricultural practices in regions with diverse cropping systems. Farmers growing more crops are more likely to exhibit high PUBs, increasing potential health and environmental risks, such as improper disposal and harm to pollinators (Mishra *et al.*, 2018; Garibaldi *et al.*, 2013). However, the lack of significant effects from education and income, contrary to expectations from prior studies (Damalas and Hashemi, 2010), suggests that local awareness campaigns or regulations in Jaipur may have standardized safety practices across socio-economic groups, a promising outcome that warrants further investigation.

The methodological approaches employed correlation analysis, SEM, and CHAID decision trees offered complementary perspectives, though each faced limitations. The SEM's poor fit indicates a need for model refinement, potentially by incorporating more indicators of PUB (e.g., frequency of application, protective equipment use, and disposal practices) and addressing multicollinearity. Similarly, the decision tree's moderate accuracy suggests that future analyses should revert to raw

categorical values for variables such as education and occupation, adjust CHAID settings to allow deeper branching, and increase the sample size to enhance generalizability (Fan *et al.*, 2015; Kline, 2015).

Despite these limitations, the findings directly inform the design of targeted training programs, fulfilling the study's fourth objective. Farmers with high PUBs, particularly those growing more crops (Node 2 in the decision tree), should be prioritized for training on IPM to reduce pesticide reliance, as well as on safe disposal methods and pollinator-friendly practices (Pretty and Bharucha, 2015; Garibaldi *et al.*, 2013). Conversely, farmers with low utilization behaviors (Node 6) can serve as peer leaders to promote sustainable practices, aligning with diffusion of innovation principles (Rogers, 2003). The puzzling lower adoption of protective equipment among educated farmers, as noted in earlier analyses, suggests a need for training that addresses overconfidence and reinforces risk awareness (Jallow *et al.*, 2017).

This study advances the understanding of safe pesticide use in Jaipur District by identifying crop diversity as a critical driver and highlighting the need for nuanced, data-driven interventions. Future research should focus on larger samples, refined statistical models, and longitudinal designs to capture changes in pesticide use behaviors over time. Policymakers and extension services in Rajasthan can leverage these findings to develop targeted programs that enhance farmer safety, reduce environmental risks, and promote sustainable vegetable farming, contributing to broader agricultural development goals in India.

DECLARATION

The authors acknowledge the use of an artificial intelligence-based language enhancement tool (Grok, developed by xAI) to improve the clarity, grammar, and readability of the manuscript. The tool was used solely for language refinement, and all scientific content, data analysis, and intellectual contributions remain the original work of the authors. The manuscript was thoroughly reviewed and edited by the authors to ensure accuracy and alignment with the research objectives.

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