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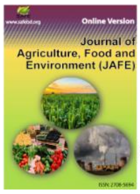

Research Article

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Influencers, barriers to adoption, and technical efficiency of integrated pest management in brinjal production: evidence from Narsingdi district, Bangladesh

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A B S T R A C T

Integrated Pest Management (IPM) was introduced to reduce dependency on pesticides; however, farmers face significant challenges in its adoption. This study evaluated IPM practices among brinjal (eggplant) farmers in Bangladesh, identifying key influencers, adoption barriers, and the technical efficiency of brinjal production. Cross-sectional data were collected from 200 randomly selected IPM-practicing vegetable farmers in two sub-districts (*upazilas*) of the Narsingdi district through face-to-face interviews using a pre-tested questionnaire from May to June 2024. Data analysis employed descriptive statistic and a Cobb-Douglas type stochastic frontier production function to assess technical efficiency and identify sources of inefficiency. The results indicate widespread adoption of sex pheromone traps (98.5%) and yellow sticky traps (91.5%) among brinjal growers. Agricultural extension officers (rated as highly influential reported by 70.5% of respondents) and IPM schools (72.5%) were the most effective influencers of IPM adoption. Major barriers to adoption included the unavailability of IPM inputs (89.0%), lack of training (86.0%), easy access to chemical pesticides (86.0%), and perceived bias in the selection for training programs (82.0%). The mean technical efficiency of brinjal production was 90.6%, indicating potential for output growth. The production function results showed that yield responded positively to increases in family labor, hired labor, power tiller cost, urea, TSP, DAP, zinc sulphate, and irrigation cost. Notably, IPM cost had a significant negative coefficient, suggesting potential pests pressure occurred and overuse or misallocation of resources. The inefficiency model revealed that contact with extension services significantly reduced production inefficiency. While specific IPM practices are being adopted, significant structural and informational barriers hinder wider implementation. The findings underscore the need for improved access to IPM inputs, comprehensive and unbiased training programs, and strengthened extension services to optimize inputs use and enhance the economic viability of IPM for Bangladeshi vegetable farmers.

INTRODUCTION

Following its independence, Bangladesh introduced pesticides to reduce crop losses and boost agricultural production. However, their overuse now poses a serious threat to the environment and public health, primarily through food contamination and direct, long-term health consequences for farmers.

IPM emerged in the 1970s as a response to the growing recognition of these adverse effects (Angon *et al.*, 2023). Prokopy & Kogan (2009) defined IPM as an approach that combines multiple techniques to maintain pest populations below economically damaging thresholds, IPM aims to reduce reliance on pesticides, thereby promoting positive economic and ecological outcomes while safeguarding farmer health. This strategy was introduced to Bangladesh through a collaborative effort between the government and the Food and Agriculture Organization (FAO), starting with a vegetable cultivation program in 1996 (Kabir & Rainis, 2015). Since then, the dissemination of IPM has been promoted by various governmental and non-governmental agencies. As Abdollahzadeh *et al.* (2015) note, understanding farmers' perceptions and knowledge is key to fostering successful adoption of IPM.

Research on IPM in Bangladesh highlights both progress and challenges. While studies confirm its benefits such as higher profitability (Akter *et al*., 2016) and significant reductions in pesticide use and cost (Rahman *et al*., 2018), the overall adoption and scaling have been slower than anticipated (Kabir & Rainis, 2013a). Factors influencing adoption include farmer age, land ownership, perceptions of IPM, and household size, and the study find only 30.0% of farmers had implemented IPM in their vegetable fields (Kabir & Rainis, 2014). Successful adoption has been linked to formal training, the influence of peer decisions (Rahman & Norton, 2019a), higher education levels, larger farm size, and greater mass media exposure (Rahman, 2020). However, a disparity between IPM personnel and the farmer population remains a barrier, indicating a need for better staff-to-farmer ratios for effective implementation (Kabir & Rainis, 2013b).

The challenges faced in Bangladesh reflect a broader global trend. IPM shows significant potential; an analysis of 85 projects in Asia and Africa revealed a mean yield increase of 40.9% alongside a 30.7% reduction in pesticide use (Pretty & Bharucha, 2015). Similar successes have been documented in Pakistan (Noman *et al*., 2024) and Cambodia (Srinivasan *et al*., 2019). Despite this, adoption in developing nations remains limited due to a lack of knowledge and training, perceived complexity, and labour requirements (Geedi & Reddy, 2023). For instance, in Nepal, only 37.0% of vegetable farmers adopted IPM, with barriers including easy access to chemical pesticides and scarcity of bio-pesticides (Shrestha *et al*., 2024). This gap between awareness and practice is common, as seen in Sri Lanka where 44.0% of farmers recognized the term IPM, but only 20.0% understood its practices (Jayasooriya & Aheeyar, 2015).

Effective dissemination models are therefore crucial. Studies highlight the importance of knowledge transfer through agricultural officers and NGOs (Khanal *et al*., 2020), structured training like Farmer Field Schools (Ali & Sharif, 2012), and the social capital within agricultural cooperatives (Ma & Abdulai, 2018; Liu *et al*., 2022). These findings demonstrate that targeted, knowledge-based extension strategies are essential for translating IPM's potential into widespread practice.

While existing research in Bangladesh has explored IPM techniques, a significant gap remains regarding its application specifically in vegetable cultivation. Previous studies have not sufficiently identified the primary influencers driving adoption or analysed the technical efficiency of IPM practices for key vegetable like brinjal (eggplant). This study aims to address these gaps by focusing on the major vegetable-producing district of Narsingdi. This study documented the spectrum of IPM methods used, identify key influencers and barriers to adoption, and evaluate the technical efficiency of brinjal production under IPM management.

MATERIALS AND METHODS

Selection of the study area and the sample

The study was conducted in the Narsingdi district, a major vegetable-producing region in Bangladesh. Two sub-districts (*upazilas*), Raypura and Monohordi, were selected based on two criteria: the total area under vegetable cultivation and the availability of Integrated Pest Management (IPM) practices. From each of these two *upazilas*, three villages were selected, resulting in a total of six villages for the study. A list of 300 IPM-practicing farmers was compiled from each *upazila*, creating a sampling frame of 600 farmers. From each list, 100 farmers were randomly selected, yielding a final sample size of 200 respondents.

Interview schedule and data collection procedure

Data were collected through face-to-face interviews with the 200 selected vegetable growers during May and June 2024. A pre-tested interview schedule was used for data collection. Prior to the main survey, the questionnaire was pre-tested with five vegetable growers in a village within the Narsingdi district; their responses were excluded from the final analysis. The interview schedule was finalized based on feedback received during this pre-test. The collected data were analysed using STATA 15 econometric software.

Data analysis

The data were primarily analysed and presented using descriptive statistic. The Cobb-Douglas type production frontier model was used both to measure the technical efficiency of brinjal farms and to determine the factors influencing their inefficiency. Technical efficiency in brinjal farms was estimated using the Cobb-Douglas type production frontier model (Aigner *et al*., 1977), specified as follows:

$$Y = f(X_i\beta_i) + \varepsilon_i \qquad i = 1, 2, \ldots\ldots n \qquad (1)$$

Here, Y denotes output, X_i is the actual inputs vector, β_i is its corresponding parameter vector, and ε_i is a two-component error term. The error term is specified as:

$$\varepsilon_i = V_i - U_i \qquad (2)$$

Here, V_i denotes the symmetric random error component, assumed to be independently and identically distributed as normal N (0, σ_v^2). U_i represents the one-sided error component, which is independently distributed from V_i and follows a normal distribution with a scale parameter (0, σ_u^2). In accordance with Jondrow *et al.* (1982), technical efficiency is estimated using the mean of the conditional distribution of U_i given ε_i, which is defined by the following expression:

$$E\left(\frac{U_i}{\varepsilon_i}\right) = \frac{\sigma u \sigma v}{\sigma}\left(\frac{f(\varepsilon_i\lambda)/\sigma}{1 - F(\varepsilon_i\lambda)/\sigma} - \frac{\varepsilon_i\lambda}{\sigma}\right) \qquad (3)$$

Here, λ is the ratio of standard deviations, defined as, $\lambda = \frac{\sigma_u}{\sigma_v}$, and σ^2 is the total variance, given by, $\sigma^2 = \sigma_u^2 + \sigma_v^2$. Furthermore, f and F represent the standard normal probability density function and cumulative distribution function, respectively, both evaluated at the point ($\varepsilon_j\lambda/\sigma$).

Farm-specific technical efficiency (TE) is measured as the ratio of observed output (Y_i) to the maximum feasible frontier output (Y_i*), attainable with the available technology. This efficiency measure, derived from Equation 3, is expressed as follows:

$$TE_i = \frac{Y_i}{Y_i{}^*} = \frac{E(Yi|ui,X_i)}{E(Yi|ui=0,X_i)} = \text{E}\ [\exp\ (\text{-}U_i)/\varepsilon_i] \qquad (4)$$

TE is a metric bounded between 0 and 1. A score of 0 denotes a fully inefficient farm, while a score of 1 represents a fully efficient one. The application of the Cobb-Douglas functional form for this type of analysis is well-established in the context of developing countries, as evidenced by its use in numerous studies (Brave-Ureta *et al.* 1997, Ajibefun *et al.* 2002, Ogundari, K. and S. O. OJO 2007, Alam *et al.* 2011, Aminu *et al.* 2013, Todsadee *et al.* 2012, Habiyaremye *et al.* 2019, Ng'Atigwa *et al.* 2022).

This research specifies the Cobb-Douglas type production frontier function for vegetable farms in the study area as follows:

$$\text{In } Y_i = \delta_0 + \delta_1 \text{ In } K_{1i} + \delta_2 \text{ In } K_{2i} + \delta_3 \text{ In } K_{3i} + \delta_4 \text{ In } K_{4i} + \delta_5 \text{ In } K_{5i} + \delta_6 \text{ In } K_{6i} + \delta_7 \text{ In } K_{7i} + \delta_8 \text{ In } K_{8i} + \delta_9 \text{ In } K_{9i} + \delta_{10} \text{ In } K_{10i} + \delta_{11} \text{ In } K_{11i} + \delta_{12} \text{ In } K_{12i} + \delta_{13} \text{ In } K_{13i} + \delta_{14} \text{ In } K_{14i} + \delta_{15} \text{ In } K_{15i} + V_i - U_i \qquad (5)$$

Where, In = Natural logarithm, Y_i = Yield of brinjal (Kg/ha), K_1 = Number of seedlings used (number/ha), K_2 = Cost of power tiller (Tk./ha), K_3 = Family labour (man days/ha), K_4 = Hired labour (man days/ha), K_5 = Urea (Kg/ha), K_6 = TSP (kg/ha), K_7 = DAP (kg/ha), K_8 = MoP (Kg/ha), K_9 = Zinc sulphate (Kg/ha), K_{10} = Gypsum (Kg/ha), K_{11} = Cow dung (Kg/ha), K_{12} = Organic fertilizer (Kg/ha), K_{13} = IPM cost (Taka/ha), K_{14} = Cost of irrigation (Taka/ha), K_{15} = land rent (Taka/ha), δ_0 = Constant, δ_i = Coefficient of parameter, i = 1,…………….,15. The error term comprises two independent components: V_i, a random noise variable that is independently and identically distributed, and U_i, a non-negative random variable that captures technical inefficiency. This specification applies to all 200 farms (i = 1, 2, ..., 200) in the sample.

Following Coelli (1995), the technical inefficiency effect, U_i, is as follows:

$$Ui = \varphi_0 + \varphi_j M_i \qquad (6)$$

M_1 = Farmer's age in years, M_2 = Farmer's years of schooling, M_3 = Farmer's farming experience in years, M_4 = Farmer's spouse education in years, M_4 = Women involvement in farming dummy variable, if farmer's spouse involved in farming is 1, 0 for otherwise. M_5 = Farmer's number of extension contact per year, M_6 = Farmer's number of IPM training received, M_7 = Brinjal cultivation of area to total farm size (%), φ_0 = Constant, the coefficients φ_j represent unknown parameters to be estimated, i = 1, ……………., j; i = 1, 2,…………, 200.

These socioeconomic variables are integrated into the model to evaluate their hypothesized effects on technical inefficiency. Furthermore, we employ a generalized likelihood-ratio test to examine the statistical presence of technical inefficiency, as defined by the following equation:

$$\lambda = -\ln\ (H_o \frac{1}{H_A}) \qquad (7)$$

Where, H_o: In the model, the inefficiency does not exist. H_A: In the model, the inefficiency exists. Apart from other physical inputs, farmers reported the costs for some production inputs, such as power tiller use, cow dung, organic fertilizer, IPM, irrigation, and land rent. This is a common practice for calculating production costs in Bangladeshi agriculture.

RESULTS

Different IPM methods used by farmers for different vegetables in the study area

The adoption of various IPM methods differed considerably across vegetable types (Table 1). Sex pheromone traps were most widely used by brinjal (eggplant) growers (98.5%), followed by cucumber (85.0%) and country bean (67.5%) growers. Usage was moderate among bitter gourd (60.5%), wax gourd (52.5%), and spiny gourd (48.0%) growers, and lowest for bottle gourd growers (35.5%).

A similar pattern was observed for yellow sticky traps, which saw overwhelmingly high adoption among brinjal growers (91.5%). Adoption was significantly lower for other crops: cucumber (43.0%), country bean (42.0%), wax gourd (37.5%), bottle gourd (31.0%), bitter gourd (26.0%), and spiny gourd (19.0%).

Among soil amendments, vermicompost was most prominent, with a high adoption rate of 60.0% for brinjal growers, followed by country bean (30.0%), cucumber (27.5%), and wax gourd (24.0%) growers. Conversely, adoption was relatively low for bottle gourd (14.5%), bitter gourd (12.5%), and spiny gourd (10.5%) growers. The use of dust from dried leaves, roots, and flowers was common, with the highest rates among brinjal (49.0%), country bean (48.5%), and bottle gourd (48.0%) growers.

Other IPM methods saw more limited use. Tricho-compost was primarily adopted by brinjal (27.5%) and cucumber (22.5%) growers, while poultry refuse application was highest among brinjal (23.0%) and wax gourd (20.0%) growers. For both of these methods, adoption rates for the remaining crops were below 17.0%.

Table 1: Different IPM method used by farmers for different vegetables in the research area

Vegetables	Sex pheromone trap	Yellow sticky trap	Poultry refuse for soil amendment	Tricho-compost	Vermicompost	Dust from dried leaves, roots and flowers
Brinjal	197.0	183.0	46.0	55.0	120.0	98.0
	(98.5)	(91.5)	(23.0)	(27.5)	(60.0)	(49.0)
Bitter gourd	121.0	52.0	19.0	12.0	25.0	46.0
	(60.5)	(26.0)	(9.5)	(6.0)	(12.5)	(23.0)
Spiny gourd	96.0	38.0	27.0	8.0	21.0	65.0
	(48.0)	(19.0)	(13.5)	(4.0)	(10.5)	(32.5)

Vegetables	Sex pheromone trap	Yellow sticky trap	Poultry refuse for soil amendment	Tricho-compost	Vermicompost	Dust from dried leaves, roots and flowers
Cucumber	170.0 (85.0)	86.0 (43.0)	21.0 (10.5)	45.0 (22.5)	55.0 (27.5)	76.0 (38.0)
Bottle gourd	71.0 (35.5)	62.0 (31.0)	23.0 (11.5)	12.0 (6.0)	29.0 (14.5)	96.0 (48.0)
Country bean	135.0 (67.5)	84.0 (42.0)	34.0 (17.0)	26.0 (13.0)	60.0 (30.0)	97.0 (48.5)
Wax gourd	105.0 (52.5)	75.0 (37.5)	40.0 (20.0)	21.0 (10.5)	48.0 (24.0)	79.0 (39.5)

Note: Each farmers used more than one IPM methods at a time in their vegetables
Figure in the parenthesis indicate percentage of total farmers

Various individuals and media influence farmers' adoption of IPM in the study area

Farmers' adoption of IPM in the study area was influenced by various sources to differing degrees (Table 2). The influence of informal and social networks was generally limited. Family members had a modest overall impact, with 39.5% of farmers reporting some level of influence (22.0% highly influenced; 17.5% influenced) and 38.0% reporting no influence. Neighbour farmers were a more persuasive source, as 61.5% of farmers were influenced by them. In contrast, relatives had a negligible effect, with 40.0% of farmers reporting no influence at all.

Formal, knowledge-based channels were the most impactful. Agricultural extension officers were highly influential, with 70.5% of farmers reporting a high level of influence. Similarly, IPM schools were a highly effective driver of adoption, influencing 92.0% of farmers to some degree (72.5% highly influenced; 19.5% influenced).

Other channels had varied success. Demonstration plots influenced nearly half of the farmers (48.0% were either influenced or highly influenced), though 31.0% were only slightly influenced. In contrast, mass media and events were largely ineffective. Television and radio failed to influence the majority of farmers (60.5%), and agricultural fairs had a limited impact, persuading only 11.5% of farmers. The influence of village cooperatives was also minimal, with a plurality of farmers (47.0%) reporting no influence. Social media had the most negligible impact, with a significant majority (64.0%) of farmers reporting it had no influence on their adoption decision.

Table 2: Various individuals and media influence farmers' adoption of IPM in the research area

Items	Highly influenced	Influence	Slightly influence	No influence
Family member	44.0 (22.0)	35.0 (17.5)	45.0 (22.5)	76.0 (38.0)
Neighbour farmer	36.0 (18.0)	87.0 (43.5)	70.0 (35.0)	7.0 (3.5)
Relatives	4.0 (2.0)	44.0 (22.0)	72.0 (36.0)	80.0 (40.0)
Agriculture extension officer	141.0 (70.5)	55.0 (27.5)	4.0 (2.0)	-
TV/Radio	-	11.0 (5.5)	68.0 (34.0)	121.0 (60.5)
IPM School	145.0 (72.5)	39.0 (19.5)	14.0 (7.0)	2.0 (1.0)
Demonstration plot	31.0 (15.5)	65.0 (32.5)	62.0 (31.0)	42.0 (21.0)
Agriculture fair	-	23.0 (11.5)	84.0 (42.0)	93.0 (46.5)
Village cooperative	15.0 (7.5)	28.0 (14.0)	63.0 (31.5)	94.0 (47.0)
Social media	9.0 (4.5)	37.0 (18.5)	26.0 (13.0)	128.0 (64.0)

Note: Figure in the parenthesis indicate percentage of total farmers

Major obstacles to adopt IPM in the vegetables field mentioned by the farmers in the study area

The primary obstacles to adopting IPM in vegetable cultivation were identified (Table 3). The most significant barrier, cited by 89.0% of farmers, was the unavailability of IPM inputs in the study area. Closely related were a critical lack of training (86.0%) and the easy availability of conventional pesticides (86.0%), which presented a major impediment. Furthermore, deficiencies in the support system were prominent: a shortage of experienced IPM trainers (82.5%) and a perceived bias in the selection of trainees by the Upazila agriculture office (82.0%) were frequently reported.

Other substantial challenges included the absence of sufficient demonstration plots (79.0%) and the discouraging effect of neighbours not practicing IPM (73.0%). The influence of pesticide sellers (68.0%) and the perception that IPM results take more time to manifest (64.0%) were also prominent obstacles. Over half of the farmers (51.5%) saw no market price premium for IPM-produced vegetables, reducing the economic incentive. Doubts about the effectiveness of IPM practices were also prevalent (44.5%). Less frequently cited barriers included a lack of coordination among neighbors and extension workers (35.5%), a general apprehension towards the method (27.5%), and, to a lesser extent, the perception that IPM is expensive (14.0%).

Table 3. Major obstacles to adopt IPM in the vegetables field mentioned by the farmers

Barriers	Yes	No
Unavailability of IPM method or instrument in the village market	178.0 (89.0)	22.0 (11.0)
Lack of IPM training	172.0 (86.0)	28.0 (14.0)
Pesticide easily availability in the village	172.0 (86.0)	28.0 (14.0)
Lack of experience trainer for IPM adoption	165.0 (82.5)	35.0 (17.5)
Biased selection of farmer for IPM training	164.0 (82.0)	36.0 (18.0)

Barriers	Yes	No
Absence of sufficient successful IPM demonstration plots	158.0 (79.0)	42.0 (21.0)
Neighbour farmer is not practicing IPM	146.0 (73.0)	54.0 (27.0)
Influence of pesticide sellers to buy pesticide	136.0 (68.0)	64.0 (32.0)
Outcome from IPM practices need more time	128.0 (64.0)	72.0 (36.0)
There is no difference of price between IPM and non-IPM vegetables	103.0 (51.5)	97.0 (48.5)
Doubt about the effectiveness of IPM practices	89.0 (44.5)	111.0 (55.5)
Neighbour farmers and extension workers not coordinating well	71.0 (35.5)	129.0 (64.5)
Fear about IPM method or technique	55.0 (27.5)	145.0 (72.5)
IPM method or technique is expensive	28.0 (14.0)	172.0 (86.0)

Note: Figure in the parenthesis indicate percentage of total farmers

Model Reliability and Diagnostic Checks

Table 4 displays that the diagnostic statistic confirm the reliability of the estimated models. In the cross-sectional study, heteroscedasticity is a severe problem in the model. So, for removing heteroscedasticity, we employed robust standard error. The low Variance Inflation Factor (VIF) values of 1.75 and 1.67 for the main and robustness check models, respectively, affirm that multicollinearity is not a concern, ensuring that the estimated coefficients are stable and interpretable. The significant values for sigma u (σ_u) and sigma v (σv) further validate the model's decomposition of the error term into a systematic inefficiency component and random noise.

Efficiency of brinjal producing farm

Table 4 shows that the estimated Cobb-Douglas type stochastic frontier production function provides critical insights into the input-use efficiency and determinants of technical efficiency in brinjal (eggplant) production. The model's high statistical significance, as confirmed by the Wald chi-square test (211.03, p<0.01 for the main model), indicates a robust fit to the data. We can say that there is no convergence issue but suggest stability. Furthermore, the highly significant lambda (λ) value of 1.37 and the result of the likelihood ratio test (51.84, p<0.01) decisively reject the null hypothesis of no technical inefficiency. This confirms that the divergence of farmers from the production frontier is not merely random noise but is systematically influenced by identifiable inefficiency factors, justifying the use of the stochastic frontier approach over a standard production function. We specified the model using a double log form.

As expected, several conventional inputs demonstrate positive and significant contributions to output. The coefficients for family labor, hired labor, power tiller cost, and irrigation cost are statistically significant at the 1% level. Higher irrigation costs, increased family labor, and hired labor are associated with greater brinjal yields. The coefficients for urea, TSP and DAP are positive and statistically significant at the 5% level. An increase in urea, TSP and DAP would lead to a corresponding increase in brinjal yield. The positive and statistically significant (at the 10% level) coefficient for zinc sulphate indicates that increased zinc sulphate leads to higher brinjal yields.

However, the estimated coefficient of MoP is negative and statistically significant at the 5% level. The negative and significant coefficient for MoP indicates that its increased application leads to a reduction in brinjal yield. This suggests that farmers are overusing MoP, thereby reducing yields.

However, the most striking finding from the main model is the significant negative coefficient associated with IPM cost. On the surface, this suggests that increased expenditure on IPM is correlated with a decrease in output, which is counterintuitive. This paradox may be explained by the fact that farmers likely increase their investment in IPM practices precisely when they face severe pest or disease outbreaks, which concurrently depress yields. In this scenario, the IPM cost acts as a mitigating investment against even greater potential losses, rather than a direct production-enhancing input like fertilizer. Its negative coefficient may therefore reflect the underlying pest pressure rather than the ineffectiveness of IPM itself.

This interpretation is strongly supported by the results of the robustness check, where the IPM cost variable was omitted. The removal of this variable led to noticeable shifts in the coefficients of other inputs, such as power tiller cost and DAP, indicating that IPM cost is correlated with other production factors. More importantly, the mean technical efficiency dropped from 0.906 to 0.882 a reduction of 2.4% when IPM was excluded from the model. This decrease is critical evidence that IPM practices are, in fact, vital for achieving high levels of technical efficiency. By omitting IPM cost, the model misattributes its positive effect on preserving output to other factors or simply fails to account for the output loss it prevents, thereby underestimating the true efficiency of farmers who employ IPM strategies. Consequently, we conclude that IPM is not a direct production input but a crucial risk-management technology that safeguards yields and sustains high operational efficiency.

Determinants of Technical Inefficiency

Table 4 also reveals that the second part of the model identifies factors influencing farmers' technical inefficiency. A negative coefficient for an inefficiency variable signifies that it reduces inefficiency, thereby improving overall technical efficiency.

Among the inefficiency factors (Equation 6), the coefficient for the number of extension contacts per year was negative and statistically significant at the 1% level. This indicates that more frequent contact with extension workers reduces farmers' inefficiency in brinjal production. Each additional extension contact per year reduces inefficiency by 0.046 units, increasing technical efficiency by approximately 4.6% for the average farm. The significant negative coefficients (-0.046 and -0.047) across both models robustly indicate that farmers who have more frequent interactions with agricultural extension services are significantly more efficient. This highlights the paramount importance of knowledge transfer, access to modern agricultural information, and technical guidance in bridging the efficiency gap between farmers. In contrast, factors such as formal education and years of farming experience were found to be insignificant, suggesting that in this context, targeted, external technical advice is more impactful than general education or experiential learning alone.

Mean technical efficiency

The mean technical efficiency of brinjal farm was 90.60%, indicating significant potential for improvement (9.40% efficiency) through enhanced management practices. Efficiency scores exhibited considerable variation across farms (Figure 1), ranging from a minimum of 48.6% to a maximum of 99.40%. The analysis unequivocally demonstrates that IPM is a critical technology for maintaining high efficiency by mitigating production risks. Furthermore, policy efforts aimed at increasing farmers' access to and frequency of contact with agricultural extension services are likely to be the most effective strategy for further enhancing technical efficiency and productivity in brinjal cultivation.

Table 4: Maximum likelihood estimates of Cobb-Douglas type stochastic frontier production model

Variables name	**Main model**		**Robustness check model**	
	Coefficient	**Robust SE**	**Coefficient**	**Robust SE**
Ln Number of seedlings used (number/ha)	-0.068	0.048	-0.088	0.057
Ln Power tiller cost (Tk./ha)	0.112***	0.042	0.133***	0.046
Ln Family labor (man days/ha)	0.074***	0.028	0.033	0.029
Ln Hired labor (man days/ha)	0.076***	0.032	0.052	0.036
Ln Urea (Kg/ha)	0.147**	0.061	0.162**	0.064
Ln TSP (kg/ha)	0.019**	0.014	0.029*	0.018
Ln DAP (kg/ha)	0.015**	0.007	0.030***	0.008
Ln MoP (Kg/ha)	-0.031**	0.017	-0.035**	0.017
Ln Zinc sulphate (Kg/ha)	0.005*	0.011	0.012	0.013
Ln Gypsum (Kg/ha)	0.003	0.008	0.002	0.008
Ln Cowdung (Kg/ha)	0.013	0.023	0.002	0.029
Ln Organic fertilizer (Kg/ha)	0.023	0.021	0.016	0.024
Ln IPM cost (Taka/ha)	-0.224***	0.034	-	-
Ln irrigation cost (Taka/ha)	0.169***	0.061	0.100	0.065
Ln land rent (Taka/ha)	0.016***	0.028	0.020	0.033
Constant	8.723	0.768	7.412***	0.797
Mean technical efficiency	0.906	-	0.882	-
Minimum technical efficiency	0.486	-	0.401	-
Maximum technical efficiency	0.994	-	0.993	-
Inefficiency variables:				
Age	0.004	0.059	0.018	0.049
Schooling	-0.004	0.082	-0.027	0.068
Farming experience	0.006	0.043	-0.013	0.041
Spouse education	-0.023	0.071	-0.022	0.062
Women involvement in farming dummy	-0.015	0.539	-0.076	0.487
Number of extensions contact per year	-0.046***	0.008	-0.047***	0.008
Number of IPM training	0.257	0.269	0.163	0.276
Vegetable cultivation of area to total farm size (%)	-0.020	0.013	-0.021	0.017
U sigma constant	-1.141	2.345	-0.477	1.984
V sigma constant	-3.820***	-	-3.690***	-
Model diagnostic statistic:				
Log pseudo-likelihood	73.5301	-	55.9206	-
Wald chi-square	211.03***	-	108.97***	-
Sigma v (σ_v)	0.1478***	-	0.1813742***	-
Sigma u (σ_u)	0.2025***	-	0.2049734***	-
Lamda ($\lambda = \frac{\sigma_u}{\sigma_v}$)	1.3697***	-	1.130113***	-
Likelihood ratio test H_0: δ_u=0 (H_0 = no inefficiency in the model)	51.84***	-	71.70***	-
Multicollinearity test:				
VIF value	1.75	-	1.67	-
Number of observations	200	-	200	-

Note: *, ** and *** indicate significance at 10%, 5%, 1% level of probability.

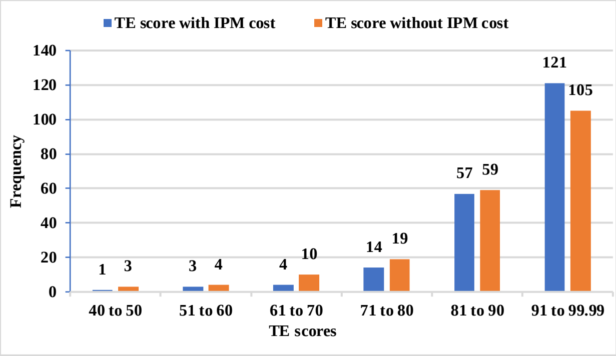

Figure 1: Frequency distribution of technical efficiency (TE) scores with or without IPM cost

DISCUSSION

This study investigated the IPM methods used by farmers and the barriers to IPM adoption among vegetable farmers in the Narsingdi district of Bangladesh. The findings revealed that sex pheromone and yellow sticky traps were the most widely used IPM methods. Farmers identified agricultural extension officers and IPM schools as their primary sources of information and motivation, indicating that adoption was overwhelmingly driven by formal, knowledge-based channels.

Overall, the adoption of IPM was unsatisfactory, pointing to a clear need for intervention. Adoption was significantly hindered by two major obstacles: the unavailability of IPM inputs in local markets and a critical lack of training. This underscores the vital role of structured, interactive training and expert guidance in facilitating behavioral change, a finding consistent with successful models like Farmer Field Schools in other regions. The significantly lower influence of mass media, social media, and informal networks suggests that broad awareness campaigns alone are insufficient to drive adoption without hands-on demonstration and expert engagement.

The study identified profound systemic barriers to wider and more effective IPM implementation. The most significant obstacle the unavailability of IPM inputs coupled with easy access to chemical pesticides point to a critical market and infrastructure failure that severely limits farmer choice. This situation was exacerbated by deficiencies in the support system, including a widespread lack of training opportunities, a shortage of experienced trainers, and a perceived bias in the selection of farmers for training programs. These barriers created a vicious cycle where limited access prevents widespread practice, which in turn stifles market development for IPM inputs and reinforces dependence on readily available chemical alternatives.

This study also investigated the technical efficiency of brinjal (eggplant) production in the study area. The Cobb-Douglas type stochastic frontier production function model indicated a mean technical efficiency of 90.6% for brinjal farms, suggesting that farmers could increase their output by up to 9.4% by optimizing their use of available resources. Farmer training is essential for the effective use of inputs to increase production. The model also identified a key factor reducing inefficiency: more frequent contact with extension officers significantly enhanced technical efficiency, highlighting its importance for problem-solving and disseminating IPM practices.

The production frontier model estimates indicate that the coefficients for hired labor, family labor, urea, TSP, zinc sulphate, and irrigation cost were statistically significant and positive, suggesting that increasing these inputs has the potential to raise brinjal yield. Conversely, the coefficients for MoP (Muriate of Potash) and IPM cost were negative and significant, implying these inputs were being overused. Rationalizing the application of all resources was therefore essential for maximizing yield.

A pivotal finding from the technical efficiency analysis was the significant negative relationship between IPM cost and yield, suggesting increased expenditure on IPM was correlated with a decrease in output, which is counterintuitive. This paradox may be explained by the fact that farmers likely increase their investment in IPM practices precisely when they faced severe pest or disease outbreaks, which concurrently depress yields. In this scenario, the IPM cost acted as a mitigating investment against even greater potential losses, rather than a direct production-enhancing input like fertilizer.

Therefore, policy efforts must move beyond promoting adoption to focus on creating an enabling environment. This includes strengthening the IPM input supply chain, reforming training programs to be more inclusive and practical, and refining extension messaging to provide clear, economics-based guidance on the optimal use of IPM inputs. By addressing these barriers and focusing on efficiency, stakeholders can enhance the economic viability and sustainability of IPM, ensuring it becomes a truly attractive and productive option for vegetable farmers in Bangladesh.

CONCLUSION AND POLICY RECOMMENDATIONS

Despite sustained initiatives by the Bangladeshi government, non-governmental organizations (NGOs), and international bodies to promote IPM among vegetable farmers, its adoption rate remains unsatisfactory. Scaling IPM practices has been hindered by a complex array of obstacles, including the limited availability of IPM inputs, a lack of comprehensive farmer training, and the pervasive ease of access to chemical pesticides.

This study demonstrates that while the adoption of specific IPM practices in the Narsingdi district is notable, overall implementation remains constrained by significant structural and informational barriers. The research confirms the paramount importance of formal extension services and IPM schools as the primary drivers of adoption, highlighting the value of direct, knowledge-based farmer engagement. However, the unavailability of IPM inputs, the easy accessibility of chemical pesticides, and substantial gaps in training create formidable obstacles for farmers. The technical efficiency analysis further reveals that while brinjal farms operate at a relatively high mean efficiency, there is still scope for improvement.

Based on these findings, a multi-faceted approach is urgently required. Government agencies and NGOs must prioritize developing robust and affordable supply chains for IPM inputs in local markets. This could involve subsidizing production, establishing distribution networks, or supporting local entrepreneurs. Concurrently, agricultural extension services require substantial strengthening. Training programs must be expanded to reach a wider audience, moving beyond potentially biased selection processes to ensure all interested farmers have access. These programs should be led by adequately trained facilitators who can provide practical, hands-on learning.

Furthermore, extension messaging must evolve from simply promoting adoption to providing precise, economically-grounded guidance. Farmers need clear information on economic thresholds for pest intervention and the optimal combination and timing of IPM techniques to maximize revenue and avoid wasteful expenditure. Establishing more IPM demonstration plots would provide tangible proof of concept and build farmer confidence. Finally, policymakers should explore mechanisms to create market incentives for IPM-produced vegetables, such as certification or branding, which could justify the initial investment for farmers and create a price premium for safer, more sustainably produced food. By implementing these recommendations, stakeholders can help transform IPM from a partially adopted alternative into a mainstream, economically viable, and ecologically sustainable foundation for vegetable production in Bangladesh.

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Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Ethical approval

For this type of research formal consent is not required

Authorship

Hasan MR: Fund acquisition, conceptualization, methodology, investigation, data collection, writing the original draft and review and editing.

Islam MA: Conceptualization, methodology, formal analysis, review and editing.

All authors are agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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