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Evaluating the Effect of Extension Advisory Services (EAS) using Economic Index Score in Aspirational Districts

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HIGHLIGHTS

- EAS significantly enhanced economic outcomes, beneficiaries reporting higher EIS (Mean = 59.69) than non-beneficiaries (Mean = 50.84), confirmed by Welch's t-test and Bayesian inference (Cohen's d = 0.61).
- The district-wise disparities in Economic Index Score (EIS) highlighted uneven extension effectiveness.
- Socio-economic and extension-related factors such as farming experience, mass media exposure, social participation and extension contact were found to have significant positive correlations with EIS.
- Despite the overall positive impact, 23 per cent of farmers fell into the low-impact category, indicating the gaps in EAS outreach and inclusiveness.

ARTICLE INFO

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ABSTRACT

The Aspirational Districts Programme (ADP) aims to uplift India's most developmentally lagging regions through targeted interventions across health, education, agriculture, and infrastructure. The study evaluated the economic impact of EAS on farmers in four aspirational districts of Bihar and Jharkhand using a novel Economic Index Score (EIS) during 2024-25. The EIS was constructed using five key dimensions viz., employment generation, asset creation, agricultural productivity, cost reduction, and value addition, capturing both the presence and duration of economic benefits from EAS. The data were collected from 320 farmers and 30 service providers personally. The statistical analysis, including Welch's ANOVA, Games-Howell post hoc tests, and Bayesian inference, revealed significant differences in EIS between beneficiary and non-beneficiary farmers, with a moderate to large effect size (Cohen's d = 0.61). The district-wise comparisons also highlighted disparities, with Muzaffarpur showing the highest economic gains and Hazaribagh the lowest. The correlation analysis identified experience, mass media exposure, social participation, and extension contact as significant predictors of EIS. The findings established that EAS plays a crucial role in enhancing rural livelihoods, yet variations across districts and farmer profiles underscore the need for context-specific, inclusive extension models.

INTRODUCTION

Agriculture continues to be the mainstay of the Indian rural economy, employing over 54.6 per cent of the total workforce and contributing significantly to national food security (Ministry of Agriculture & Farmers Welfare, 2023). Despite rapid economic growth in some sectors, a large proportion of India's rural population remains economically vulnerable, particularly in backward and underdeveloped

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regions. These disparities are most pronounced in the Aspirational Districts, identified by the NITI Aayog in 2018 as part of the Aspirational Districts Programme. The program targets 112 districts across the country that lag in key socio-economic indicators, including health, education, agriculture, financial inclusion, and basic infrastructure (NITI Aayog, 2022). In many of these districts, concentrated in states like Bihar, Jharkhand, Uttar Pradesh, Chhattisgarh, and Odisha, agriculture is often characterized by low productivity, fragmented landholdings, inadequate irrigation and limited access to extension and market services. Farmers in these regions are highly dependent on monsoon rainfall, suffer from irregular income, and have poor access to institutional credit and technological innovations (World Bank, 2021). Moreover, the persistence of poverty and lack of diversification in income sources further increases the economic vulnerability of rural households (Chand et al., 2017). While various national-level schemes aim to enhance farmer welfare, such as PM-KISAN, Soil Health Card, Kisan Credit Card, and Pradhan Mantri Fasal Bima Yojana, their effectiveness often varies based on the socio-economic status of the beneficiaries. Most studies examining rural livelihoods rely on discrete variables like income, landholding, or education levels in isolation. However, there is a critical need for a composite and systematic framework to quantify and understand the economic realities of farmers, especially in these development-deficient districts. In response to this gap, the present study developed an Economic Index Score, a composite measure to assess the effect of extension advisory interventions. This decision was grounded in the understanding that while income is a critical indicator, it alone does not capture the multifaceted nature of economic status, particularly in rural and developing contexts. The income can be highly variable, seasonal, and often inaccurately reported, making it an unreliable sole indicator for understanding household economic conditions (Deaton, 1997; Filmer & Pritchett, 2001). The dimensions were chosen to collectively represent the core pathways through which extension advisory services interventions translate into tangible economic gains for rural households. Understanding rural livelihoods through this economic lens is essential not only for targeted policy formulation but also for prioritizing interventions under the Aspirational Districts Programme.

Looking ahead, the use of composite indices can be extended to longitudinal monitoring of livelihood changes over time, assessment of program impact and identification of region-specific development bottlenecks. The findings of this study are also expected to contribute to the broader policy discourse on doubling farmers' income, building rural resilience and reducing regional disparities as envisioned under the National Policy for Farmers and SDG Goal 1 & 2 viz., no poverty and zero hunger respectively (Bhavani, 2023).

METHODOLOGY

The study was conducted in Bihar and Jharkhand, selected purposively from India's eastern region due to their high number of aspirational districts and socio-economic relevance. A multi-stage sampling technique was adopted. Two aspirational districts were randomly selected from each state namely, Hazaribagh & Lohardaga in Jharkhand and Muzaffarpur & Gaya in Bihar. From each district, two blocks and subsequently two villages per block were randomly selected, totalling 16 villages. From each village, 20 farmers were randomly selected, giving a total of 320 farmer respondents. Additionally, 30 service professionals were purposively selected, making the total sample size 350. Economic Index Score (EIS) was employed as a composite measure to assess the economic well-being of rural households in aspirational districts. Recognizing the limitations of income as a sole indicator, owing to its variability and inaccuracy in rural settings, a multidimensional approach was adopted. The EIS incorporates five key dimensions of economic benefit that reflect the tangible impact of extension advisory services interventions namely, employment generation, asset creation, agricultural productivity, cost reduction and value addition. To quantify perceived economic impact, a standardized five-point ordinal scale was used, based on the duration of benefit. The respondents scored each dimension from 0 (no benefit) to 4 (benefit for more than 5 years). This method captures both the presence and longevity of economic gains, offering a detailed representation of perceived impact from the extension advisory services. The maximum possible score per respondent was 20 (5 indicators × 4) and the minimum was 0. The EIS was calculated using the formula:

$$EIS = \frac{\text{Obtained Score}}{\text{Maximum Score}} \times 100$$

This yielded a standardized score between 0 and 100 for each respondent, representing the extent of perceived economic wellbeing. The respondents were subsequently categorized into low, moderate and high economic impact groups using the cumulative square root frequency method for further comparative analysis. The Games-Howell post hoc test was used for pairwise comparisons due to unequal variances across the districts. A Welch's *t*-test was conducted to examine significant differences in the EIS between farmers who were beneficiaries of Extension Advisory Services and those who were not. The Cohen's d test was used to quantify the effect size between two groups, measuring the magnitude of the difference between their means. For the purpose of evaluating the effect of EAS, farmers were classified into two groups based on their major source of advisory services. Farmers were assigned to the beneficiary group (treatment) if over 60 per cent of their farming decisions were influenced by formal channels such as KVKs, ATMA, SAUs or ICT-based platforms. Conversely, those relying primarily on informal sources like peer networks or input dealers were classified as non-beneficiaries (control group). Based on the review of literature and theoretical framework, the following hypotheses were formulated to guide the analysis.

It was hypothesised that there is no significant difference in the EIS between beneficiary and non-beneficiary farmers EAS (H_o). whereas as an alternate there is a significant difference in the EIS between beneficiary and non-beneficiary farmers of EAS (H_1):

$$H_o : \mu_1 = \mu_2,\ H_1 : \mu_1 \neq \mu_2$$

RESULTS

Categorization and distribution of farmers based on their economic index score

Table 1 presents the categorization of farmers based on their EIS using cumulative square root frequency into three groups, namely low, moderate, and high impact. The analysis of EIS across four aspirational districts viz., Gaya, Hazaribagh, Lohardaga, and Muzaffarpur, revealed significant differences in perceived economic benefits derived from extension advisory services. Using Welch's ANOVA (Table 2), which accounts for unequal variances, a statistically significant difference was observed among the districts, F (3,175.4) = 7.71, p = 0.0000724 with a partial eta squared (η^2_ρ) value of 0.12, indicating a moderate effect size. As represented in Figure 1, the mean EIS was highest in Muzaffarpur, followed by Gaya, Lohardaga and lowest in Hazaribagh. Table 3 presents the pairwise Games-Howell post hoc test, which confirmed that these differences were statistically significant, particularly between Muzaffarpur and Hazaribagh. A Welch's *t*-test was conducted to examine whether there is a significant difference in the Economic Impact Score (EIS) between farmers who were beneficiaries of Extension Advisory Services and those who were not (Table 4) and the results revealed a statistically significant difference in mean EIS between the two groups: ($t_{Welch(318)} = 5.43$, $p = 1.10 \times 10^{-7}$). The mean EIS for beneficiaries was significantly higher than that of non-

Table 1. Categorization and distribution of farmers based on their economic index score

Category	Range	Frequency	Percentage
Low Impact	<42.29	74	23.125
Moderate Impact	42.29-71.44	198	61.875
High Impact	>71.44	48	15
Total	320	100	

Table 2. Test Summary of district-wise comparison of EIS

Component	Details
Test Used	Welch's ANOVA
Test Statistic	*F* (3, 175.4) = 7.71
p-value	7.24×10^{-5}
Effect Size	Partial Eta Squared (η^2_ρ) = 0.12

Table 3. Games-Howell Post-hoc Test – Pairwise District Comparison of EIS

District Pair	Mean Difference	p-value (adjusted)
Muzaffarpur vs Hazaribagh	10.81	p < 0.001 (Significant)
Muzaffarpur vs Lohardaga	6.87	p < 0.05 (Significant)
Muzaffarpur vs Gaya	3.74	Not Significant
Gaya vs Hazaribagh	7.07	p < 0.05 (Significant)
Gaya vs Lohardaga	3.13	Not Significant
Lohardaga vs Hazaribagh	3.94	Not Significant

Table 4. Welch's t-test comparison of EIS between beneficiary and non-beneficiary groups

Test Parameter	Value
Test Used	Welch's t-test
Test Statistic	$t_{(318)} = 5.43$
p-value	1.10×10^{-7}
Effect Size	Cohen's *d* = 0.61 *(moderate)*
Sample Size	*n* = 320

beneficiaries as presented in Figure 2. The effect size, measured by Cohen's *d* = 0.61, suggested a moderate to large effect, indicating practical significance. Alzahrani et al., (2023) assessed the efficacy of public extension services and found similar results. The 95 per cent confidence interval for the difference in means [5.49, 11.79] further confirmed the robustness of this result.

Testing hypothesis

The log Bayes Factor value of $\log_{10}(B_{01}) = -11.55$ strongly supports the alternative hypothesis (H_1). A negative log Bayes Factor (especially below -2 or -3) indicates increasing evidence against the null hypothesis. In this case, Bayes Factor value is considered very strong evidence in favour of a real difference between the groups of beneficiaries to the non-beneficiaries. Since

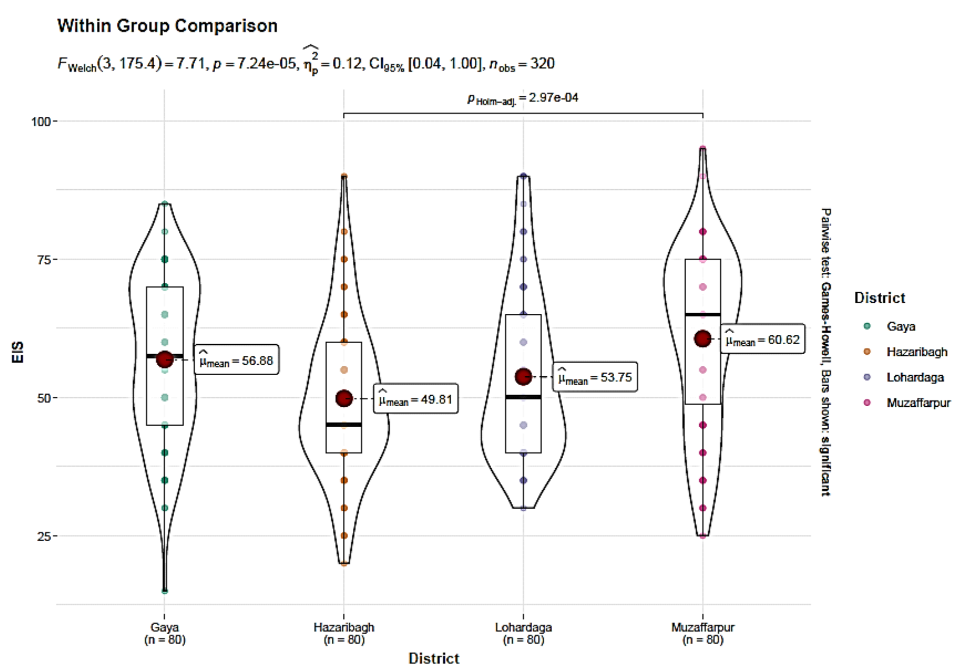

Figure 1. Violin plot representation of EIS among the respondents across the districts

Figure 2. Violin plot representation of EIS of beneficiaries and non-beneficiaries

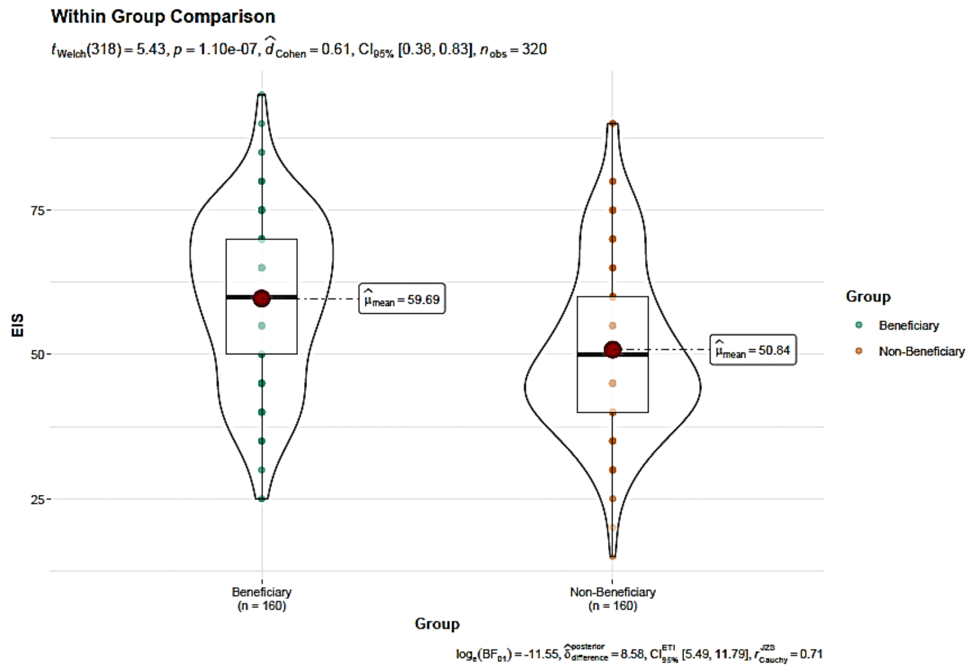

Table 5. Influence of Farmer Attributes and Extension Factors on EIS

Variable	Correlation with EIS	p-value (Sig.)	Interpretation
Mass Media Exposure	0.348	0.000**	Moderate positive relationship with EIS, even after controlling for other variables.
Age	0.043	0.443	No significant relationship with EIS.
Experience	0.407	0.000**	Strongest predictor among all; experience significantly influences EIS.
StandardAnimal Unit	0.143	0.011*	Weak positive but significant effect.
Social Participation	0.288	0.000**	Moderate positive effect on EIS.
Extension Contact	0.348	0.000**	Also has a moderate and significant positive impact.

*Significant at 5% LOS, **Significant at 1 % LOS

the mean EIS for beneficiaries (μ = 59.69) is higher than that of non-beneficiaries (μ = 50.84), we can confidently conclude that receiving extension advisory services had a positive and significant economic impact on farmers. These results are in line with Singh et al., (2015) & Wossen et al., (2017).

Influence of farmer attributes and extension factors on EIS

As represented in Table 5, the correlation between various farmer attributes and EIS concluded that experience, extension contact, and mass media exposure had significant and moderate to strong positive influence on EIS, while age shows no significant relationship. The standard animal unit and social participation also contribute positively, though to a lesser extent. These findings are in line with Priscilla et al., (2021).

DISCUSSION

The analysis of EIS revealed significant variations in the effectiveness of Extension Advisory Services across aspirational districts in Bihar and Jharkhand. As supported by the findings of Jaiswal et al., (2018), the majority of respondents fall under the moderate impact category, which suggested that while EAS contributes positively to farmers' economic wellbeing, the benefits remain uneven and often limited in scale. Only 15 per cent of farmers reported high impact, pointing to the presence of enabling factors such as strong extension-farmer linkages, better information access or higher social participation that are not uniformly available. Tayang et al., (2024) also confirmed the positive impact of EAS on rural livelihoods. Kumar et al., (2022) observed the economic impact of the *Meghdoot* agro-advisory application in terms of the yield performance of barley and wheat in the case of registered and non-registered farmers. Using a quantitative approach, they highlighted that access to advisory services directly correlates with improved income levels, when services are tailored to local conditions and farmers' specific needs. The mean EIS differs significantly among the four districts. Muzaffarpur was showing the highest economic gains, followed by Gaya, Lohardaga and Hazaribagh. This trend implies that local contextual factors such as institutional efficiency, service delivery models and infrastructure play a critical role in shaping EAS outcomes and reflect the differences in the effectiveness and accessibility of extension advisory services. These findings align with Chand et al., (2015), who argue that districts with better ICT use, proactive extension mechanisms and stakeholder linkages report higher service effectiveness. Conversely, the low performance of Hazaribagh supports Nagar et al., (2021), who attributed regional disparities to poor targeting, limited field outreach, poor relevance of advice, lack of follow-up and institutional trust deficits. A statistically significant difference in EIS is also observed between beneficiary and non-beneficiary farmers. The beneficiaries report a higher mean compared to non-beneficiaries, with a moderate effect size, indicating that EAS contributes meaningfully to economic wellbeing. Similar results were found by Venu et al., (2013), who evaluated ATMA's effectiveness in two Indian districts, Ahmednagar (Maharashtra) and Dahod (Gujarat) by comparing outcomes for ATMA and non-ATMA farmers. The results showed a significant increase in crop yields, returns and farm income in Ahmednagar. This difference is further substantiated by Bayesian inference, which provides decisive evidence in favour of a real difference between the groups. These results corroborate earlier findings by Davis et al., (2018) who emphasize that timely, context-specific extension information improves farm decision-making, productivity and income. The observed district-wise variation suggests that location explains part of the impact, but individual-level socio-economic factors such as education, landholding size, group membership and frequency of extension contact are also influential. This supports Singh et al., (2023), who highlighted the multifactorial nature of EAS outcomes. Education and land holding size were observed linked with the adoption of weather-based agro-advisories by Kumar et al., (2021). Interestingly, a substantial minority falls into the low impact group, suggesting systemic exclusions possibly due to poor awareness, marginalization, or service inadequacy. These outliers indicate a critical gap that calls for targeted interventions, especially in underserved areas and among vulnerable groups. While the findings generally align with prior research, they also highlight persistent inequities in extension reach and impact. The positive outcomes among beneficiaries emphasize the potential of EAS, yet the underperformance in certain districts and among non-beneficiaries indicates structural and delivery-related weaknesses. The variation also underscores the importance of contextually adaptive, location-specific extension models. Adhiguru et al., (2009), highlighted how regional disparities in infrastructure and extension personnel availability could cause differential access and utilisation levels. Similarly, Yaseen et al., (2021); Sentibenla & Jha (2024) also noted that location-specific factors often determine the success or failure of extension interventions.

Overall, the study established a clear relationship between access to EAS and economic wellbeing among farmers. It founded a consistent trend of higher EIS among beneficiaries and in districts with stronger institutional setups. However, exceptions in the form of low-impact respondents and inter-district disparities signal the need for inclusive and differentiated extension strategies. The strengthening EAS through improved targeting, regular follow-ups and participatory approaches can ensure broader and more equitable impacts, particularly in the developmentally lagging aspirational districts.

CONCLUSION

This study established that access to quality extension services leads to significant improvements in the economic well-being of farmers in underdeveloped regions. The evidence confirmed that farmers receiving advisory support showed higher gains in employment, productivity, asset creation, cost efficiency and value addition than those without such access. The developed economic assessment tool effectively captures these outcomes and reveals important variations across districts and farmer profiles. These findings underscore that timely, inclusive and context-specific extension services are essential for achieving equitable rural development. The results validate the core hypothesis that targeted extension interventions positively influence economic outcomes and support the broader goals of agricultural transformation and regional equity.

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