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Agricultural Information Transfer among Tribal Farmers of Malkangiri Using Machine Learning

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HIGHLIGHT

- Personal localite contacts emerged as the most effective channel with the lowest information transfer gap of 34.61 per cent.
- Farming experience was the strongest predictor, contributing 36.80 per cent to model predictive power among tribal farmers.
- Ridge regression (CV R^2 = 0.503) outperformed random forest in generalisation, making it optimal for tribal extension programme design.

ARTICLE INFO

Keywords: Agricultural information transfer, Machine learning, Random forest, SHAP values, Tribal farmers.

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ABSTRACT

The study was carried out in 2026 to examine the extent of agricultural information transfer and the determinants of agricultural information transfer among tribal farmers of Malkangiri district of Odisha. Four blocks were selected purposively, and 30 farmers were randomly selected from each block through a multistage random sampling technique, constituting a total sample of 120 respondents. Primary data were collected using a pre-tested and structured interview schedule. Data were analysed using descriptive statistics random forest regression algorithm in Google Colaboratory, with SHapley Additive explanations values computed for explainable feature-level attribution. The agricultural information transfer was low to moderate across all five channels, ranging from the highest mean score for personal locality contact (1.96) to the lowest for private sector engagement (1.18; gap = 60.76%). Experience on farms and age were the most significant predictors, together explaining 66.77 per cent of the model's feature importance, with education having little influence. The training performance of the random forest model was good (R^2 = 0.9159), while it acknowledges the 0.4877 gap and attributes it to sample size and RF's sensitivity.

INTRODUCTION

Agricultural information is the lifeblood of rural transformation, as it helps farming communities access better technologies, improve the productivity of their operations, and maintain their livelihoods (Bhagat et al., 2004; Nain et al., 2015; Sandeep et al., 2022; Sanju et al., 2025). Even with significant investment in public extension systems, the lack of information continues to marginalise tribal communities in geographically isolated areas of India (Bora & Mahanta, 2022). This is more pronounced in the scheduled tribal belts of South Odisha, where physical isolation, linguistic diversity, and lack of extension staff with required training make the job difficult. The southernmost district of Odisha, namely, Malkangiri, is a typical example of the condition and has 58 per cent tribal population, with 52.24 per cent literacy rate (Panigrahi, 2019; Tripathy & Ranjitha, 2022).

For instance, Malkangiri's tribal farming communities, primarily Koya, Bonda, and Kondh communities, do not rely on formal extension services to provide agricultural guidance and information; instead, they use informal peer networks and

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traditional knowledge, as demonstrated by Ghosh et al. (2025). Although a number of government schemes, such as the Special Programme for Promotion of Integrated Farming and the Odisha Millet Mission, have enhanced crop diversification in some blocks, the transfer of technologies varies across the region (Odisha Department of Agriculture, 2022). Distress migration, limited access to extension workers, a lack of communication tools in tribal languages, and weak market linkage continue to hinder the smooth dissemination of agricultural information to communities (Panda et al., 2019; Jat et al., 2021; Niranjan et al., 2023; Saha et al., 2024).

Machine learning methods offer substantial promise for advancing the evidence base on agricultural information transfer. Conventional regression approaches, while widely employed in extension research, are limited in their capacity to model the complex, non-linear interactions among socioeconomic, psychological, and contextual variables that jointly determine a tribal farmer's information-seeking behaviour (Shukla et al., 2024). ML algorithms-including random forest, gradient boosting, and regularised regression-can simultaneously handle high-dimensional predictor spaces, rank feature contributions through SHAP values, and yield cross-validated performance estimates that reliably generalise to new populations (Khatri et al., 2024; High et al., 2025). These capabilities are particularly valuable for designing targeted, resource-efficient extension strategies in data-scarce tribal districts.

Although growing literature documents information-seeking behaviour among tribal farmers in North-East India (Syiem & Raj, 2015) and central India (Jat et al., 2021), empirical research applying ML-based modelling to agricultural information transfer in the tribal districts of southern Odisha remains conspicuously absent. The present study was therefore undertaken to assess the level of agricultural information transfer among tribal farmers in Malkangiri district.

METHODOLOGY

The study was conducted in the Malkangiri district of Odisha in 2026. Malkangiri district, situated in the southern part of Odisha, is home to a predominantly tribal population engaged in subsistence agriculture, making it contextually appropriate locale for examining agricultural information transfer. The district comprises 7 blocks, of which four blocks, namely Khairaput, Korukonda, Malkangiri and Mathili, were purposively selected on account of their significantly higher concentration of tribal farming households. Random sampling was used to select respondents in two stages. For the first stage, two villages were randomly selected from each selected blocks, resulting in eight study villages. In second stage, a complete enumeration of tribal farm households in each village was carried out to prepare the sampling frame. Subsequently, using random sampling, 15 farmers were selected from each village, yielding a final sample of 120 tribal farmers. Primary data were collected through personal interviews using a pre-tested, structured interview schedule. The interview schedule comprised items pertaining to 14 independent variables: age, education, occupation, livestock ownership, annual income, family size, family type, type of house, size of land holding, type of land holding, farming experience, social participation, innovativeness, and risk orientation. The dependent variable was the level of agricultural information transfer. Based on the frequency of access to and use of different sources of information, the information dissemination was measured using a three-point rating scale with response options of "Regular", "Occasionally" and "Never" (Shivamogga & Pujar, 2018). Accordingly, weighted mean scores were calculated for each information transfer dimension to facilitate comparison of their relative effectiveness. To quantify the extent of deficiency in information dissemination, the Information Transfer Gap (ITG) was computed using the following formula, ITG (%) = [(3 − Mean Score)/3] × 100, where 3 represents the maximum obtainable score on the scale. Additionally, a random forest regression algorithm was applied to model non-linear interactions among the 14 predictor variables and to generate SHAP (SHapley Additive exPlanations) values for explainable, feature-level attribution of model output. The RF model comprised 200 decision trees with a maximum depth of 10 and was implemented using Google Collaboratory (Google Colab), a cloud-based Python programming environment, through the scikit-learn library (Pedregosa et al., 2011). Model performance was evaluated using coefficient of determination (R^2), mean absolute error, root mean square error, and five-fold cross-validation R^2 to guard against overfitting. Statistical significance was set at the 5 per cent probability level throughout the analysis.

RESULTS

Table 1 presents the statement-wise mean scores and information transfer gap (ITG) percentages for the five identified channels of agricultural information transfer among tribal farmers of Malkangiri. Overall, the mean scores (ranging from 1.18 to 1.96 across the five statements) on a three-point scale. Transfer through personal localite was found to be the best channel, with a mean score of 1.96 and a corresponding information transfer gap of 34.61 per cent, indicating that personal localite or informal face-to-face interaction within the community remains the most predominant channel of agricultural information flow among tribal farmers. Extension participation (mean = 1.91; gap = 36.48%) and extension contact (mean = 1.85; gap = 38.38%) were in the substantial range, while very little information transfer occurred through mass media (mean = 1.79; gap = 40.42%). All four channels had gaps of more than 34 per cent, however, indicating significant room for improvement in disseminating information, even in channels that perform relatively well.

The most shocking discovery was the very poor mean score (1.18) and the corresponding information transfer gap (60.76%) in the private sector and agri-input companies with the lowest rank among all five channels. This is a clear indication that the role of

Table 1. Statement-wise Information Transfer Level with Mean Score and Information Transfer Gap (%)

Item	Information Transfer	
	Mean	Gap %
Mass Media Exposure	1.79	40.42
Transfer by Personal Localite	1.96	34.61
Extension Contact	1.85	38.38
Extension Participation	1.91	36.48
Private Sector/Companies	1.18	60.76

Table 2. Evaluation Metrics of the Random Forest Model

Statement	R^2 Score	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Mean Absolute Percentage Error (MAPE)
Training set performance	0.9159	0.7076	0.8816	0.0155
Test set performance	0.5943	1.3508	1.8077	0.0288
Full dataset performance	0.8604	0.8362	1.1293	0.0182

the private sector in the agricultural information system of tribal Malkangiri is negligible, due to the area's limited commercial potential and the purchasing power of tribal farming households.

Table 2 shows the evaluation indicators of the random forest (RF) regression model on training set, test set and full data set. The following four metrics were used to assess the models: coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE).

The model showed a good fit in the training set, with an R^2 of 0.9159, meaning that the model accounted for 91.59 per cent of the variance in the scores of agricultural information transfer during the learning phase. The MAE, RMSE, and MAPE were 0.7076, 0.8816, and 0.0155 (1.55%) respectively, which indicated that the average prediction error was still acceptable on training data.

On the test set, however, model performance declined noticeably, with R^2 dropping to 0.5943, MAE rising to 1.3508, RMSE to 1.8077, and MAPE to 0.0288 (2.88%). An R^2 value of 0.9159 when the model was trained, and 0.5943 when tested, indicates a substantial training–test gap... consistent with significant overfitting explains the mechanistic reason (14 predictors, n=120, max depth 10). This is a known limitation of tree-based ensemble methods when applied to relatively small datasets, as the 120-respondent sample used in the present study may be insufficient for the model to fully capture generalisable patterns without overfitting.

On the full dataset, the RF model achieved an intermediate R^2 of 0.8604, with MAE of 0.8362, RMSE of 1.1293, and MAPE of 0.0182 (1.82%), reflecting an overall moderate-to-good level of predictive accuracy when all 120 observations were included. Taken together, the evaluation metrics confirm that while the random forest model possesses strong learning capacity, its generalisation to new tribal farmer populations' remains moderate. These findings justify the complementary use of ridge regression, which recorded superior cross-validation R^2 (0.503) and offered greater interpretability for extension planning, as discussed subsequently.

Figure 1 shows the performance of the random forest (RF) model as tested on the three measures cross-validation R^2, mean absolute error (MAE), and root mean square error (RMSE) for five-fold cross-validation (CV).

Regarding cross validation R^2, the scores varied from a minimum of 0.2909 in Fold 5 to a maximum of 0.4837 in Fold 4 and the mean CV R^2 was 0.4282. Model learning was consistently the same for folds 1-4 with R^2 values between 0.4523 and 0.4837, showing that the model learned similar information across most of the data partitions. The depressed CV R^2 of 0.2909 in Fold 5 warrants explicit justification. With a total sample of only 120 respondents partitioned into five folds, each validation fold contains approximately 24 observations. Small fold sizes of this magnitude render CV R^2 estimates highly sensitive to the distributional composition of the withheld subset. This interpretation is corroborated by Fold 5's concurrent MAE of 1.4547 and RMSE of 1.8500–both the lowest recorded across all five folds confirming that the model's absolute prediction errors were actually smallest in this fold. The apparent paradox of low R^2 alongside low MAE/RMSE is therefore a statistical artefact of reduced outcome variance in the Fold 5 holdout, not evidence of model misspecification or localised instability.

The MAE scores across the five folds ranged from 1.4547 (Fold 5) to 1.8539 (Fold 2), with a mean MAE of 1.6921. Folds 1, 2, and 3 had MAE values higher than the mean (1.7993, 1.8539, and 1.7987, respectively) while Folds 4 and 5 were lower than the mean (1.5539 and 1.4547, respectively) showing that the model had smaller absolute prediction errors in the latter folds, but Fold 5 had the lowest value of R^2 (0.650). These seemingly conflicting results indicate that the model had relatively smaller absolute error in Fold 5, but its ability to explain the overall variance in the fold was limited, possibly because of limited range or fewer variability in the outcome variable in the fold.

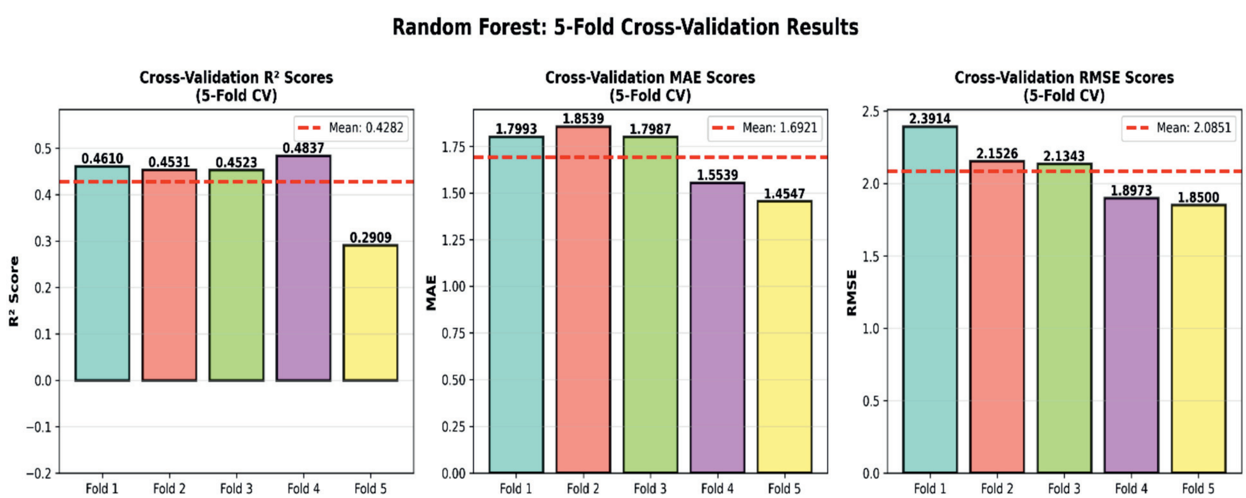

Figure 1. 5 Fold Cross Validation Scores

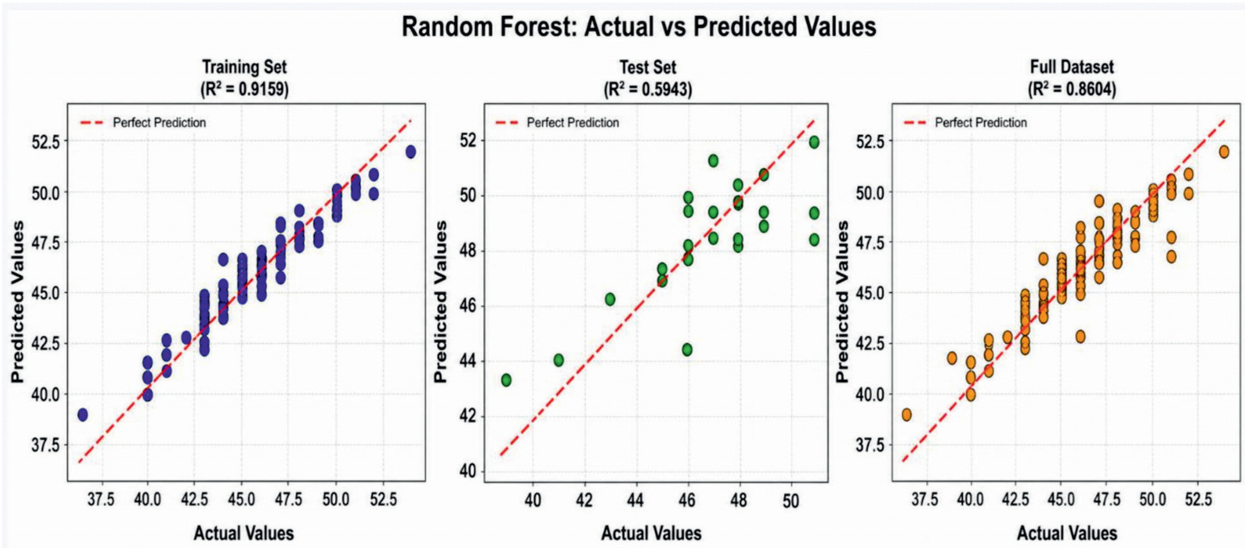

Figure 2. Actual vs Predicted

The RMSE values were generally similar, ranging from 2.3914 in Fold 1 to 1.8500 in Fold 5 and an average value of 2.0851. The Folds 4 and 5 recorded the lowest RMSE values (1.8973 and 1.8500 respectively), showing that the prediction errors produced in these partitions were relatively smaller when compared with Fold 1 which recorded the highest RMSE value of 2.5769.

Overall, the results of the cross validation confirmed the substantial to consistent generalisability of the RF model across all five folds, with mean CV R^2 (0.4282), mean MAE (1.6921), and mean RMSE (2.0851) all suggesting the RF model explained around 42.82 per cent of variance in the agricultural information transfer scores on unseen data, with the mean error in prediction being approximately 1.69 units. The CV R^2 was also relatively lower than the full data set R^2 (0.8604), which further supported the degree of overfitting that was seen in the Table 2.

The Figure 2 presents a comprehensive performance evaluation of a Random Forest regression model through actual versus predicted value scatter plots across three distinct data partitions, revealing critical insights into the model's predictive capabilities and generalization performance. The three-panel visualization employs a consistent format where the x-axis represents actual observed values and the y-axis shows model predictions, with a red dashed diagonal line indicating perfect prediction (where predicted values exactly equal actual values). The Training Set (left panel, blue points) exhibits remarkably strong performance with an R^2 of 0.9159, demonstrating that the model explains approximately 91.6% of the variance in the training data, with data points clustering tightly along the perfect prediction line across the entire range from approximately 37.5 to 52.5. This near-excellent fit suggests the Random Forest algorithm has effectively captured the underlying patterns and relationships within the training data. However, the Test Set (middle panel, green points) tells a dramatically different story, with R^2 plummeting to 0.5943, indicating that only about 59.4% of variance is explained when the model encounters previously unseen data. The substantially increased scatter from the perfect prediction line, particularly noticeable at the lower end of the actual value range (around 40-44), reveals systematic prediction errors and highlights the model's difficulty in generalizing beyond its training experience. Several conspicuous outliers appear where the model either significantly overestimates or underestimates actual values, suggesting the presence of complex patterns or feature interactions that the model failed to learn in a generalizable manner. The Full Dataset panel (right, orange points) combines both training and test observations, yielding an intermediate R^2 of 0.8604, which represents a weighted average performance across all data but masks the concerning performance discrepancy between training and testing phases. The stark 32-percentage-point drop in R^2 from training to test (0.9159 to 0.5943) is a classic signature of overfitting, where the model has essentially memorized noise and specific idiosyncrasies of the training data rather than learning truly generalizable relationships, causing it to perform poorly when faced with new observations that contain different random variations or slightly different patterns. This overfitting could stem from several potential issues: the Random Forest may have too many trees with insufficient regularization, the training set might be too small or unrepresentative of the broader population, important features may be missing that would help the model generalize, or there may be fundamental differences in the distributions between training and test sets that the model cannot bridge.

Figure 3 presents the feature importance scores of all 14 predictor variables derived from the random forest (RF) model, ranked in descending order of their relative contribution to predicting agricultural information transfer among tribal farmers of Malkangiri. Feature importance in the RF framework reflects the mean decrease in node impurity attributable to each variable across all decision trees in the ensemble, thereby providing a data-driven ranking of predictor variables independent of linear assumptions.

Farming experience emerged as the most influential predictor of agricultural information transfer, recording the highest importance score of 0.3680, which accounted for approximately 36.80 per cent of the total predictive contribution of the model. This finding indicated that the number of years a tribal farmer had been engaged in agricultural activities was the determinant of the extent to which agricultural information was transferred, suggesting that experiential

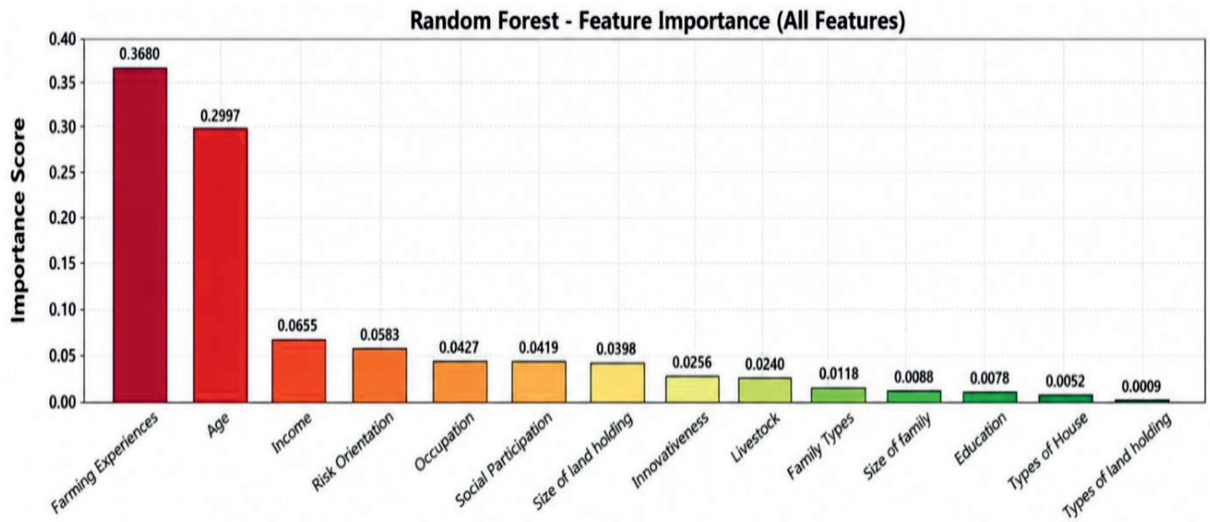

Figure 3. Feature Importance

learning accumulated over years of farming practice substantially enhanced a farmer's capacity to seek, process, and relay agricultural information within the community. Age ranked second in importance with a score of 0.2997 (29.97%), underscoring the combined dominance of farming experience and age, which together accounted for 66.77 per cent of the model's total feature importance.

The remaining 12 variables collectively contributed only 33.23 per cent of the total feature importance, highlighting the overwhelming dominance of farming experience and age in predicting information transfer. Among the remaining predictors, income ranked third with an importance score of 0.0655 (6.55%), followed by risk orientation (0.0583; 5.83%), occupation (0.0427; 4.27%), social participation (0.0419; 4.19%), and size of land holding (0.0398; 3.98%). These variables occupied an intermediate tier of importance, suggesting a secondary but non-negligible role in shaping the agricultural information transfer behaviour of tribal farmers. Innovativeness (0.0256) and livestock ownership (0.0240) contributed marginally to the model's predictive power, while family types (0.0118), size of family (0.0088), education (0.0078), and types of house (0.0052) recorded very low importance scores, indicating minimal independent influence on information transfer once the dominant variables were accounted for. Types of land holding recorded the lowest importance score of 0.0009, contributing less than 0.1 per cent to the model's overall predictive capacity, suggesting that the nature of land tenure had virtually no bearing on information transfer behaviour among the tribal farmers studied.

The colour gradient of the bars in Figure 3, transitioning from deep red for the highest-importance variables to yellow-green for the lowest, visually reinforced the sharp hierarchical differentiation among predictor variables. The steep decline in importance scores from farming experience (0.3680) and age (0.2997) to income (0.0655) and beyond reflected a highly skewed distribution of predictive contributions, a pattern consistent with earlier machine learning-based studies in agricultural extension research which reported that experiential. These results further validated the regression findings, wherein farming experience and age emerged as the two statistically significant predictors with the largest standardised coefficients in the multiple linear regression model.

The SHAP (SHapley Additive exPlanations) summary bee swarm plot for random forest model shows the direction, magnitude, and distribution of each predictor variable's contribution towards predicting agricultural information transfer among tribal farmers of Malkangiri district. One dot in the plot represented one farmer's observation, with the horizontal position of the dot corresponding to the magnitude and direction of its effect on the model's prediction for that observation, or the SHAP value. Dots placed to the right of the zero baseline indicated a positive effect on predicted information transfer scores, and dots placed to the left indicated a negative effect on predicted information transfer scores. Each dot was colour-coded with the value of the feature associated with the observation, and this colour code of the dots allowed the direction of effect to be interpreted along with the nature of the feature value causing the effect.

The farming experience variable showed the greatest horizontal range in SHAP values of any of the 14 variables, ranging from around –4.0 on the negative side to well beyond +3.0 on the positive side, indicating its importance as a predictor in the model. The direction of the colour pattern for farming experience showed a clear, consistent pattern: dots with higher farming experience values were predominantly on the positive side of the baseline, suggesting that increased farming experience significantly increased farmers' predicted information transfer scores. On the other hand, low farming experience farmers (blue dots) were placed on the negative side which suggested that their limited experience resulted in lower predicted scores.

Age also showed a similar pattern, with an increasing number of red dots located to the right of the zero line and blue dots to the left of the zero line indicating a consistent positive relationship between older age and greater predicted information transfer. SHAP values for age ranged from around –3.0 to above +2.5 indicating that age is the second most influential variable, and in line with the feature importance results shown in Figure 3.

Income showed a rather different picture, with red points representing the high income farmers concentrated on the negative side of the baseline and blue points representing the low-income farmers on the positive side. The inverse relationship suggests that

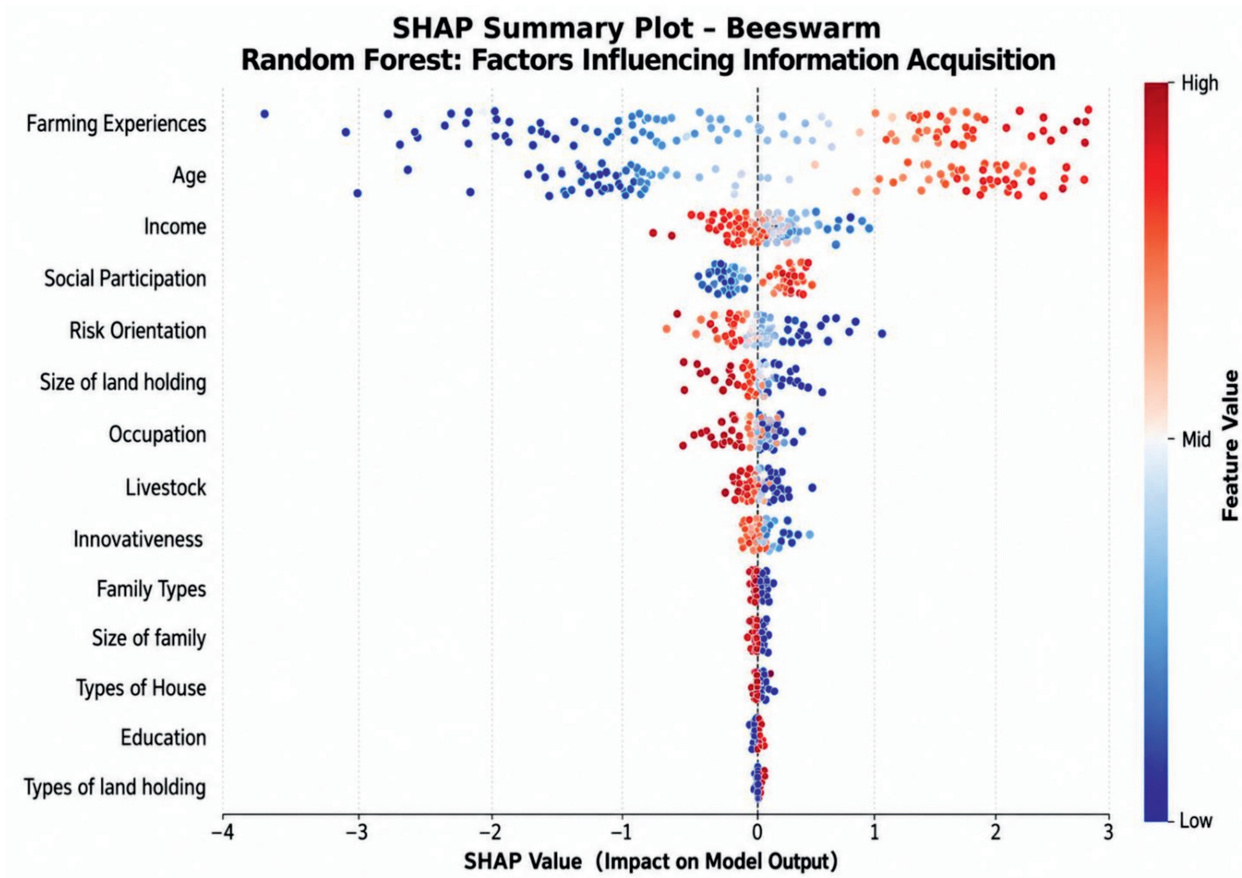

Figure 4. SHAP Summary Plot

a higher income level was correlated with lower predicted information transfer scores, which implies that wealthier tribal farmers may be less dependent on community-based or extension mediated sources of information and may get agricultural information from private or commercial sources. The direction of social participation showed clear positive data with a majority of observations (red dots) to the right of zero, indicating that higher levels of social participation facilitated greater information transfer. The data of the risk orientation presented a mixed distributional pattern, with high and low feature values being found on each side of the baseline, suggesting a more complex non-linear relationship between risk orientation and information transfer, which may not have been adequately captured by simple regression coefficients.

All the remaining variables, with the exception of innovativeness and size of family, had small SHAP value ranges close to the SHAP baseline of zero and the dots of all observations were tightly grouped around zero. This pattern indicates that these variables had relatively low and inconsistent contributions to the prediction of agricultural information transfer across the range of observed values. Education had a significantly smaller spread than the other lower-tier variables, with the shapes of most observations falling within a range of SHAP values from –0.5 to +0.5.

DISCUSSION

The findings of the present study reveal that agricultural information transfer among tribal farmers of Malkangiri is low to moderate across all five channels, with personal localite contacts recording the highest mean score (1.96) and the smallest information transfer gap (34.61%), while private sector and agri-input companies register the most critical deficiency (mean = 1.18; gap = 60.76%). This pattern aligns with Rajkhowa and Qaim (2021) and Coggins et al. (2022), who establish that geographically isolated and socially marginalised farming communities depend predominantly on informal interpersonal networks rather than formal or market-mediated channels for agricultural information, owing to structural barriers such as sparse extension coverage, linguistic diversity, and limited digital access. The finding corroborates Jat et al. (2021), who similarly documented that tribal farmers in backward districts of India rely on community-based contacts as their primary information source.

Farming experience emerges as the single most influential determinant of agricultural information transfer, accounting for 36.80 per cent of the random forest model's predictive contribution, with SHAP values confirming a consistent positive directional effect across all 120 observations. Age contributes an additional 29.97 per cent, and together these two variables explain 66.77 per cent of the model's total feature importance. Income presents an inverse relationship with information transfer, wherein high-income farmers are associated with negative SHAP values, indicating a suppressive effect on predicted scores. This counterintuitive finding agrees with Rajkhowa and Qaim (2021), who report that higher-income smallholder farmers substitute public extension information with market-mediated advisory services, reducing their engagement with community-based channels. Social participation (importance = 0.0419) displays a consistent positive SHAP direction, validating the argument of Begho (2025) and Lai (2025) that collective institutional engagement through farmer networks enhances information access and relay capacity. Risk orientation presents a non-linear, mixed directional pattern, suggesting its effect is substantial by contextual variables such as income and experience - a nuance that linear regression alone cannot reveal.

CONCLUSION

The study reveals that the farming experience and age were the two key factors affecting agricultural information transfer among the tribal farmers of Malkangiri, with almost two-thirds of the total predictive power of the model, whereas income, social participation and risk orientation had a secondary impact. Private sector involvement is still underutilised, while personal locality contacts are the most effective channel of information. This is because the machine learning method used in the study has high learning ability, while its generalisation ability is substantial, which underscores the importance of an interpretable regularised regression method for designing extension programmes. Targeted extension strategies that prioritise experienced and older farmers as community information leaders, strengthen farmer group participation, and diversify channel outreach beyond informal networks are essential for bridging the persistent information transfer gap in tribal Malkangiri.

DECLARATIONS

Ethics approval and informed consent: The respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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