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Modelling Livelihood Security of Tribal Farmers in South Odisha using Machine Learning

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HIGHLIGHTS

- Livelihood security declines with age, with a sharper drop among older farmers.
- Strong self-confidence markedly elevates livelihood security across farmer profiles.
- Better farm management practices boost security and cushion age-related disadvantages.
- Innovative tendency helps, but less than self-confidence and management.

ARTICLE INFO

Keywords: Livelihood security, Tribal farmers, South Odisha, Random Forest, SHAP.

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ABSTRACT

Tribal farming systems ensure livelihood security through complex socio-economic and behavioural interactions that defy simple linear models. The study analysed primary data collected through simple random sampling method from 180 households in Gajapati and Rayagada districts of Odisha during 2023-24 to analyse the Livelihood Security score using a Random Forest regression. Out-of-bag validation demonstrated model stability with an R^2 of approximately 0.865 using around 400 trees. The age was the most significant predictor, followed by self-confidence, with smaller contributions from management orientation and innovative proneness. One- and two-dimensional partial dependence outcomes highlighted non-linear age effects and interactions, indicating that increased confidence and enhanced management capacity improve predicted livelihood security across all age groups. These results suggest actionable strategies for agricultural extension: implementing confidence-building and management training tailored to life-stage constraints could yield substantial benefits. Limitations include the correlational nature of the data and the reliance on partial dependence.

INTRODUCTION

One of the key issues that tribal farming families face in the eastern hill and forest ecosystems of India is livelihood security. This challenge is exacerbated by factors such as rain-fed agriculture, fragmented and uneven land tenure, and limited access to markets. In South Odisha, the situation is further complicated by hilly terrain, inadequate irrigation facilities, high transaction costs for inputs and outputs, and commodity price volatility (Das et al., 2025). Households also encounter environmental threats like erratic rainfall, dry spells, and degraded commons, which interact with social limitations such as lack of information, limited extension services, and insufficient credit (Kumari et al., 2024). Livelihood security is not determined by a single factor. Instead, it results from the combined arrangement of household resources, human capital, and behavioural-psychological motivations that influence the adoption of better practices and the ability to cope with shocks (Pal et al., 2017; Suman et al., 2025).

Traditional empirical methods have helped identify correlations between welfare and technology adoption in smallholder contexts.

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These methods often assume linearity and additivity, which limits their ability to capture the threshold effects and interactions present in actual farming systems. The impact of an additional unit of land or income can vary significantly depending on a household's managerial capacity or confidence. The benefits of information from mass media can differ based on education levels or age-related preferences. These non-linearities and interactions are particularly significant in tribal areas, where livelihood strategies are diverse and context-dependent (Kerketa et al., 2025). There is a strong case for using analytical tools that can flexibly approximate complex response surfaces while remaining transparent enough to guide extension programming (Prusty et al., 2025).Most Odisha-focused livelihood security studies are macro/district-level and descriptive rather than household-level with predictor modelling (Pani & Mishra, 2022).While machine learning is widely used in agriculture, applications to household livelihood security and especially those using interpretable ML remain scarce (Ryo, 2022). Interpretable-ML works demonstrate context-dependent thresholds and interactions in rural systems, yet the studies are rarely leveraged to reveal capital access complementarities in tribal livelihood security (Rana et al., 2024).

This research employs a Random Forest (RF) modelling framework to investigate the factors that influence Livelihood Security scores among tribal farmers in South Odisha. RF is particularly suited for this analysis as it can handle mixed data types, model non-linear relationships and interaction effects without requiring predefined functional forms, and offers built-in validation and training-set evaluation (Breiman, 2001). To enhance the RF model beyond mere prediction and support decision-making, the integration of Permutation Feature Importance, Shapley Additive Explanations (SHAP), and Partial Dependence/Individual Conditional Expectation (ICE) plots, including two-dimensional surfaces, is used to visualise important interactions (Goldstein et al., 2015). This interpretability suite allows to elucidate not only which factors are significant but also how they influence livelihood security across the observed range (Lundberg & Lee, 2017).

The study enhances household-level analysis of livelihood security in the tribal context by modelling the livelihood security score using Random Forest regression evaluated on a held-out test set. It provides interpretable evidence on the relative influence, direction, & non-linear thresholds of capital, utilising SHAP & ICE.

METHODOLOGY

The study employed a correlational design to model the determinants of Livelihood Security among tribal farming families in South Odisha during 2023-24. Primary data were collected following simple random sampling through a structured interview schedule administered to 180 households of Gajapati and Rayagada districts of Odisha. The interview schedule assessed socio-demographic, resource, and psycho-behavioural variables commonly utilised in agricultural extension research, including age, education, family size, livestock possession, landholding, farming system practised, annual income, social participation, mass media utilisation, self-confidence, innovative proneness, economic motivation, scientific orientation, and management orientation. The dependent variable was the composite Livelihood Security.

Standard reproducible steps were followed in data preparation. Continuous variables were checked for outliers and converted into numeric categorical variables using one-hot encoding. Records lacking values in analysis fields were removed through listwise deletion, resulting in a stable modelling sample. The dataset was randomly split into a training set (80%) and a test set (20%) with a fixed seed to ensure replicability.

A Random Forest (RF) regressor was chosen as the primary predictive model due to its capability to capture non-linearities and higher-order interactions without stringent parametric assumptions. Hyperparameters were configured to a medium tree size (300-400) using out-of-bag (OOB) R^2 stabilisation, with bootstrap sampling enabled. The performance on the held-out test set was reported using R^2 and RMSE to estimate generalisation.

To numerically assess the relative importance of predictors, the Permutation Feature Importance was calculated using the test data. For local-to-global interpretability, SHAP was used to summarise the direction and magnitude of individual features' effects on households. To visualise marginal responses and potential interactions, Partial Dependence (PDP) plots and Individual Conditional Expectation (ICE) graphs were created for key predictors, as well as two-dimensional PDP surfaces for selected pairs. A one-way ANOVA, accompanied by Levene's test for homogeneity of variance, was utilised to examine categorical variables against Livelihood Security where appropriate (Levene, 1960). Analyses were conducted using Python, with scikit-learn for training RFs and calculating permutation importance; shap for generating SHAP visualisations; matplotlib for visualisation; and stats models/ scipy for inferential tests.

RESULTS

The Random Forest model effectively reproduces the observed Livelihood Security scores in the held-out training set (Figure 1). The data points were closely clustered around the 1:1 line throughout the observed range, indicating that the model was well-calibrated and not simply a tracking model. The gradient of the cloud of points relative to the 45-degree line suggests minimal systematic bias; households in both high and middle ranges were neither consistently over- nor under-predicted. A small number of points at the upper end did not deviate from the diagonal, indicating

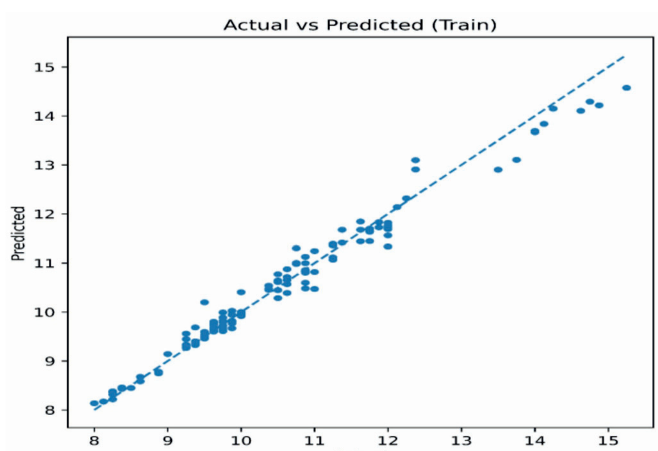


Figure 1. Training-set Actual vs Predicted for Livelihood Security

some shrinkage at the extremes. The spread of points did not significantly increase with higher scores, aligning with an approximation of homoscedastic errors in the training data. These findings demonstrated that the model provides precise and consistent forecasts of livelihood security for tribal agricultural families in South Odisha, characterised by a smaller error magnitude (RMSE) and mostly non-systematic errors.

The generalisation performance of the Random Forest improved with the size of the ensemble, eventually levelling off during out-of-bag (OOB) validation (Figure 2). The model's out-of-sample performance was tested, yielding an RMSE of 0.2264. The OOB R^2 exhibited a slight decrease from 0.8164 at 50 trees to 0.8159 at 100 trees, then recovered to 0.8171 at 150 trees and rose sharply to 0.8241 at 200. Performance continued to improve, reaching 0.8263 at 300 trees, 0.8284 at 400 trees, and 0.8295 at 600 trees. The incremental gain beyond 300 trees was less than 0.0033, and beyond 400 trees was less than 0.0012, indicating a practical plateau around 300–400 trees. Therefore, n_estimators = 400 was adopted for subsequent analyses. Thus, the OOB curve indicated that ensemble sizes of approximately 300-400 trees were sufficient for optimal generalisation, and larger forests did not provide significant additional value for this dataset.

The permutation analysis of the training data ranked predictors based on the mean change in predictive score resulting from permuting each variable, with the precise values displayed at the ends of the bars (Figure 3). The most significant predictor was age, with a value of 0.8616, followed by self-confidence at 0.1694. The second tier included management orientation (0.0718) and innovative proneness (0.0314). The next set of predictors showed relatively minor contributions: mass media utilisation (0.0165), scientific orientation (0.0117), economic motivation (0.0113), and education (0.0069). On the left side of the distribution, predictors with values below 0.005 included annual income (0.0048), livestock possession (0.0038), social participation (0.0027), land holding (0.0019), farming system practised (0.0016), and family size (0.0014). The bars illustrated a steep gradient, with age (0.8616) nearly five times more influential than self-confidence (0.1694) and over an order of magnitude greater than any other predictors below 0.07. This distribution featured a long tail of small values and no negative bars, as shown in the figure, with a strict descending order. These values represented the perturbation-based significance of each predictor in the training set, clearly visualised.

The SHAP beeswarm plot ranks features by their overall impact in descending order, as illustrated in Figure 4. Age ranked highest, followed by Self Confidence, Management Orientation, and Innovative Proneness, with the remaining predictors following in decreasing order. Age exhibited the widest spread of points on the horizontal axis, indicating the most extensive contribution range among all features. Self Confidence had the next widest spread, while the other features displayed narrower distributions. In terms of directionality, more Age values (red points) were located on the negative side of the SHAP axis (left of zero), whereas more Self Confidence values (red points) appeared on the positive side (right of zero). Management Orientation and Innovative Proneness had smaller clusters of points compared to the top features, but some noticeable positive shifts were observed at higher values. Features lower in the ranking showed narrow clusters around the zero value, which was expected for variables that contribute less compared to the top predictors. All observations in the figure were based on the held-out model, with colour encoding (blue = low, red = high) representing the value of each feature, and horizontal positioning reflecting the signed SHAP value (negative = decrease in predicted Livelihood Security; positive = increase), as visually represented.

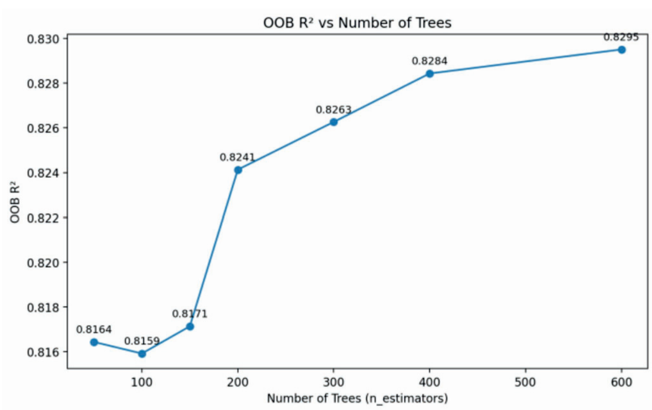


Figure 2. Out-of-bag (OOB) R^2 versus Number of Trees in the Random Forest

Figure 3. Permutation Feature Importance on the Training Set

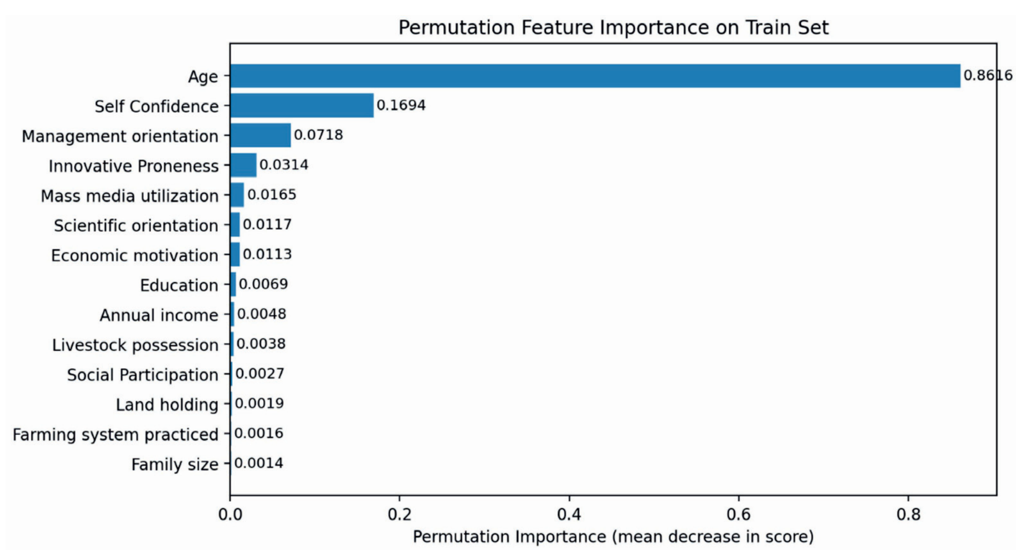
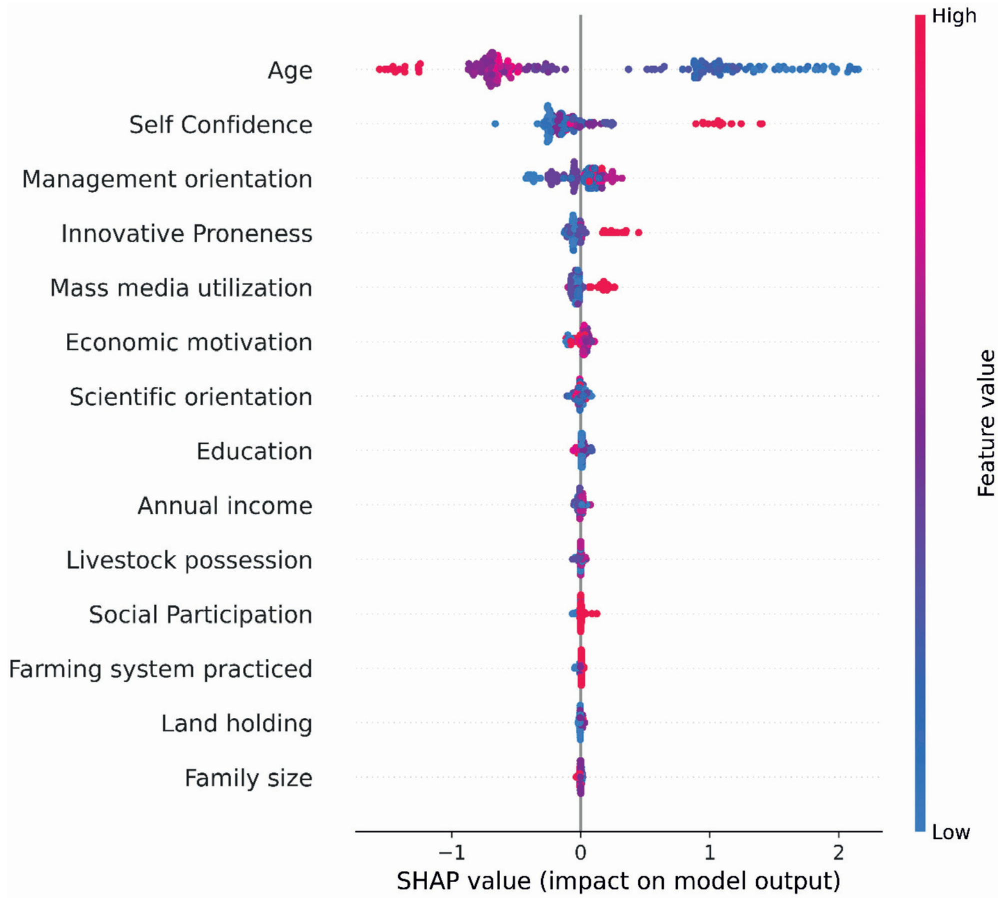


Figure 4. SHAP Summary (Beeswarm) for the Random Forest Model



The marginal responses of the model were clearly defined and supported by data (represented by rugs on the x-axes) across the one-dimensional partial-dependence profiles with ICE overlays. In Figure 5a (Age), the average curve displayed a non-linear, stepped decline: it remained relatively flat until the late 30s/early 40s, then dropped sharply in the early to mid-40s, and decreased again around age 60, after which it stabilised at a lower level. The ICE lines clustered closely around the mean curve, indicating that this pattern was consistent across households. Figure 5b (Self Confidence) showed a monotonically increasing average partial dependence throughout the relevant range, with a noticeable uplift in the curve during the mid-teens. The ICE lines exhibited a parallel upward shift, suggesting consistent gains among respondents within the supported range. In Figure 5c (Management Orientation), the average curve was slightly elevated across the observed scores, with minor variations between ICE profiles. So the shift along the management orientation scale was positive but subtle.

Figure 6a (Age x Management Orientation) illustrates that the surface decreases with age across nearly all levels of management orientation. An increase in management orientation raises the surface for a given age. The highest labelled contours are observed at younger ages, with values ranging from 11.82 to 11.24 in the late 30s to early 40s, declining to 10.66 to 10.08 in the mid-40s to 50s, and further dropping to 9.50 by the late 60s to 70s. The iso-lines in this panel are nearly vertical, indicating that age primarily drives the gradient, while the management orientation elevates the overall level without altering the age trend. Figure 6b (Age x Self Confidence) shows that higher self-confidence correlates with a higher surface at a given age, with younger ages yielding elevated projected values. The highest values are found in the upper-left quadrant (younger age, high confidence), with figures of 13.27, 12.50, and 11.74. These values decrease to a range of 10.98 to 10.21 in the early to mid-40s and approach 9.45 by age 60. The tilted contours reflect the additive contributions of both variables, showing the highest predictions in the high-self-confidence/low-age group and the lowest in the low-self-confidence/high-age group. In Figure 6c (Self Confidence x Management Orientation), the surface exhibits a higher magnitude on both axes, which are relatively low in the bottom-left corner. The magnitude of the predictions increases with either predictor. The middle range is concentrated between 10.45 and 11.01, while the upper right reaches 11.29. The iso-lines are approximately diagonal, indicating that changes in either self-confidence or management orientation lead to similar improvements. A combination of both factors results in the highest predicted scores within the observed ranges.

DISCUSSION

The Random Forest approach effectively described livelihood security among tribal farming households in South Odisha. The performance on the held-out training set was exceptionally high, confirming that the variation in the livelihood security score was accurately captured. The results align with the Sustainable Livelihoods Framework, where households combine human (education, self-confidence, management orientation), social (group

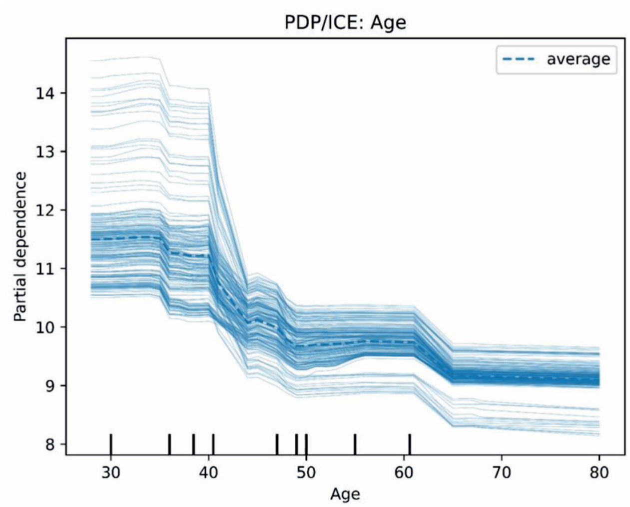


Figure 5a. Partial Dependence with Individual Conditional Expectation Plot for Age

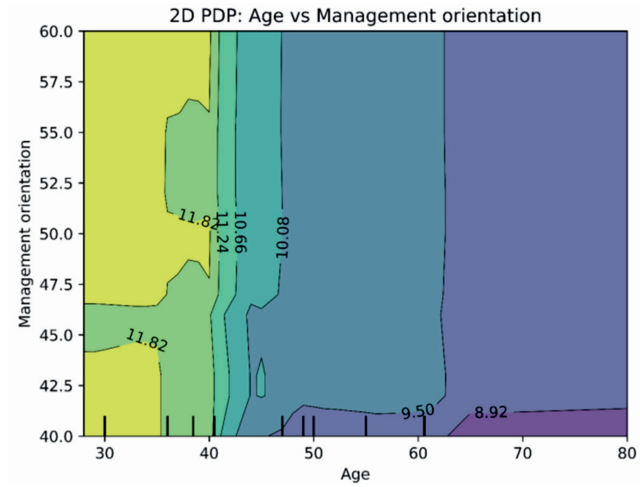


Figure 6a. Two-Dimensional Partial Dependence of Livelihood Security: Age × Management Orientation

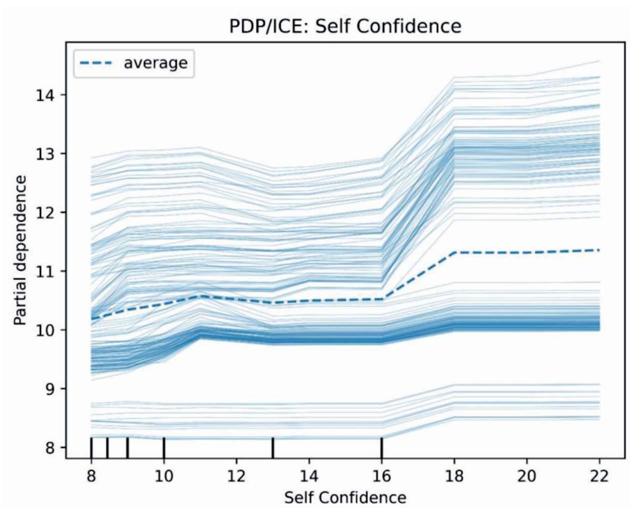


Figure 5b. Partial Dependence with Individual Conditional Expectation Plot for Self Confidence

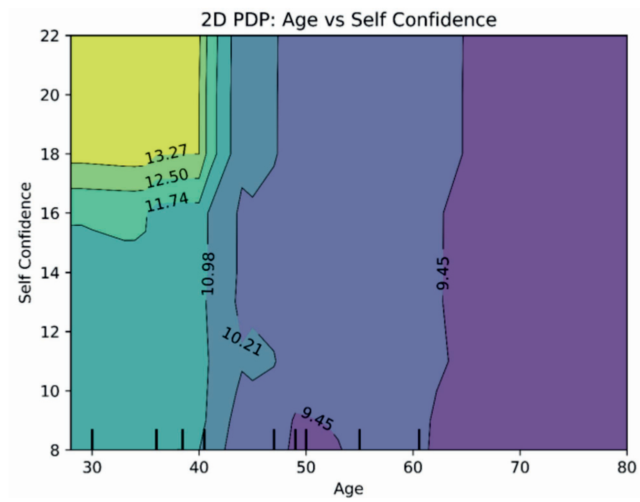


Figure 6b. Two-Dimensional Partial Dependence of Livelihood Security: Age × Self Confidence

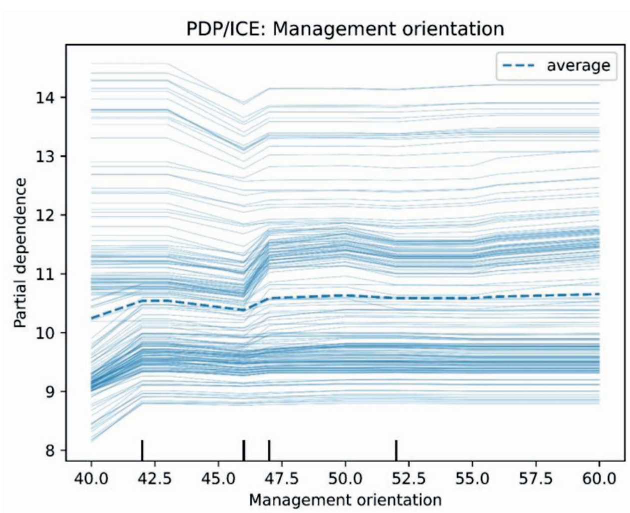


Figure 5c. Partial Dependence with Individual Conditional Expectation Plot for Management Orientation

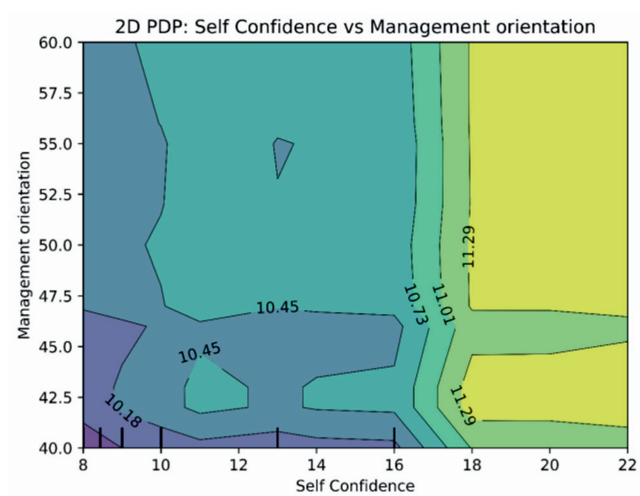


Figure 6c. Two-Dimensional Partial Dependence of Livelihood Security: Self Confidence × Management Orientation

participation), physical (irrigation, infrastructure), and financial capitals (asset/credit access) to pursue strategies that enhance livelihood security (Amghani et al., 2025). The model's non-linear response patterns suggest threshold effects followed by plateaus, consistent with capability perspectives in which small increments in key capitals move households past functional thresholds. These thresholds are plausible within the context of livelihoods, reflecting the combined effects of physical ability, caregiving demands, risk aversion, and varying access to opportunities and services throughout different life stages (Zhang et al., 2024). The uniformity of the ICE traces around the Age PDP suggested that this pattern was widespread among households, rather than limited to a small group.

Self Confidence was identified as the second significant factor, exhibiting a consistently positive relationship. The PDP/ICE profile for Self Confidence showed continuous increases, and the SHAP beeswarm indicated that higher self-confidence led to upward predictions in the sample. This aligns with field experiences in extension work: self-efficacy likely drives the adoption of recommended practices, readiness to engage in markets, and resilience in the face of climatic or price shocks (Mallick et al., 2025). There were also positive, albeit smaller, effects from management orientation and innovative inclination (Panigrahi et al., 2024). Although these factors contributed less than Age and Self Confidence, their directionality suggested that managerial skills and openness to new ideas remain valuable for enhancing livelihood security.

The interaction between age and self confidence indicated that the age-related decline in security could be partially offset by higher confidence levels. Similarly, the interaction between Age and Management Orientation suggested that greater management skills positively influenced security predictions at any age. The Self Confidence and Management Orientation interaction implied a complementary relationship, with households exhibiting both traits achieving the highest predicted scores. These interactions hold practical significance for program design: training investments can yield greater returns when confidence-building and managerial skill development are integrated and tailored to the life-stage challenges faced by older farmers (Lekang et al., 2016; Lekang et al., 2017; Saha et al., 2024).

Minor variables such as mass media use, economic motivation, and education received low permutation scores (Satapathy et al., 2024). This does not imply insignificance; rather, in the context where Age and psychosocial factors are considered, these variables contributed little incremental predictive value (Ruzzante et al., 2021). They may also have mediated their effects through the behavioural constructs already present in the model. Interpretation of these findings should be tempered by several limitations. While the sample size was adequate for exploring tree ensembles, it limited the investigation of rarer interactions and could inflate the variance in permutation estimates for low-signal features. Although PDPs are feature-independent, the ICE overlays and two-dimensional surfaces addressed some of these issues; Accumulated Local Effects (ALE) plots would serve as a valuable robustness check (Apley & Zhu, 2020). All measurements reflect observations at a specific time, and seasonal dynamics or policy shocks were not captured.

The most effective strategies may involve extension programs that combine confidence-building with management training while addressing the unique challenges faced by older farmers (Baul et al., 2024). Specific mentoring, peer-focused producer groups, and practical modules on planning, record-keeping, and market engagement could translate these relationships into tangible improvements in livelihood security (Magakwe et al., 2025).

CONCLUSION

This study's primary objective was to use random forest regression and interpretable machine learning approaches to estimate the factors that influence livelihood security among tribal farmers in South Odisha. This analysis revealed the livelihood security of tribal farming households and it was effectively modelled using a Random Forests approach, achieving a stable out-of-bag performance with an R^2 of 0.828 at around 400 trees. The age, self-confidence, and management orientation significantly shape livelihood security, with confidence-building and managerial capacity emerging as crucial levers to mitigate age-related declines. The livelihood security is not merely a function of resource endowment but is deeply influenced by psychosocial and behavioural factors. The findings suggest the adoption of targeted techniques such as experiential learning modules, role-play exercises for decision-making, farmer-to-farmer mentoring, and structured record-keeping workshops to build confidence and strengthen confidence building.

DECLARATIONS

Ethics approval and informed consent: The research was conducted in accordance with institutional guidelines and approved by all the authors. Ethical approval was obtained from all the participants, and informed consent was obtained from all participants before the study commenced.

Conflict of interest: The authors declare that there are no conflicts of interest in conducting this research study. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare that during the preparation of this work, they thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

Authors' Contribution: This work was carried out in collaboration between all the authors. Authors 1 and 2 collected the data, and Authors 3 and 4 performed the statistical analysis. The study was conceptualized, tabulated, interpreted, and the final draft of the manuscript was prepared by Authors 5, 6, and 7. All authors read and approved the final manuscript.

Data Availability Statement: The data that support the findings of this study are available upon reasonable request from the corresponding author.

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