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Exploring Livelihood Structures of Paddy Farmers in Koraput District of Odisha

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HIGHLIGHT

- Income, livestock and landholding jointly define the primary wealth dimension among farmers.
- PC1 (35.9%) separated older experienced farmers from younger educated farmers.
- PC2 (17.0%) quantified land, income and livestock inequality.
- PC3 (9.7%) captured behavioural differentiation in risk and innovation.
- Innovativeness and risk orientation emerged independent of wealth status.

ARTICLE INFO

Keywords: Livelihood, Paddy farmers, Principal component analysis, Risk orientation, Innovativeness.

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ABSTRACT

Despite the economic centrality of paddy cultivation in tribal districts of Odisha, empirical understanding of the latent socio-economic structures shaping farmers' livelihoods remains limited, with most studies relying on descriptive profiling rather than multivariate dimensional analysis. The study addresses that gap by applying Principal Component Analysis (PCA) to primary data collected in 2025 from 120 paddy farmers across four blocks of Koraput district, Odisha. Thirteen continuous socio-economic variables and five categorical attributes were transformed through one-hot encoding and standardized prior to analysis. The first principal component (35.9% variance) revealed an experience–education gradient distinguishing older, highly experienced but less formally educated farmers from younger, more educated counterparts. The second component (17.0% variance) represented a wealth–resource axis defined by income, livestock holdings, and land size. These components explained 52.9% of total variance, while subsequent components captured behavioural heterogeneity in risk orientation, innovativeness, and social participation. The findings demonstrate that livelihood differentiation in tribal paddy systems is structured along distinct socio-economic and behavioural axes rather than being uniform. By empirically identifying these gradients, the study provides a robust analytical foundation for designing stratified extension, credit, and capacity-building interventions tailored to differentiated farmer typologies in vulnerable agrarian regions.

INTRODUCTION

Paddy cultivation is one of the most vital agricultural activities in the world, serving as a primary source of food, employment, and livelihood security for millions of people, particularly across Asia and in countries like India where it plays a central role in agrarian economies. The term "paddy" refers to two species: *Oryza glaberrima,* which has many cultivated variants in West Africa and *Oryza sativa*, which comprises all paddy variations in Asia, Europe and America (Manful & Graham-Acquaah, 2016; Bharath et al., 2024). Odisha's agrarian economy and rural livelihood are primarily

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dependent on paddy agriculture. Rice or paddy occupies 45% of all farmed land and employs more than 60% of the state's labour force, demonstrating its supremacy as the staple cereal and a vital source of food (Rout et al., 2025).

Approximately 94% of the state's total grain output comes from the 4.4 million hectares of paddy farming in Odisha, which makes up 91% of the cereal land. Odisha contributes 5.5% of India's total rice production (Saha et al., 2005). The production choices of the farmers and their ability to adopt new technology are influenced by their socioeconomic factors. Education, landholding size, income, family structure, social participation, inventiveness and risk-taking are some of the elements that have a significant impact on access to resources and receptivity to extension programs (Nayak, 2025). According to empirical data, smallholders' poverty is frequently prolonged by low asset ownership, weak market ties and a lack of institutional support, particularly in rainfed and tribal areas (Birthal et al., 2014). Despite many governmental initiatives aimed at boosting agricultural growth and farmer welfare, Odisha's backward districts, such as Koraput, continue to exhibit lower production and greater livelihood risk (Gual & Das, 2025).

In fact, rice is the most prevalent crop in Koraput's Jeypore tract, accounting for more than 40% of the farmed area (Chatterjee et al., 2025). This illustrates the paddy agro-ecological suitability for the area as well as its importance for local livelihood, culture and food security. Furthermore, it highlights the need for ecological sustainability through sustainable agriculture and organic farming, which reduce chemical inputs and support long-term soil and ecosystem health (Singh et al., 2024; Thangjam & Jha, 2024). Farmers' lives and agricultural productivity are greatly influenced by their social status. Several socioeconomic factors, such as income level, landholding size, education and credit availability affects a household's capacity to invest in inputs and adopt improved practices (Touch et al., 2024; Yadav et al., 2025). By improving farmers' comprehension and use of contemporary methods, education plays an empowering role. Similarly, increasing farm resilience and productivity necessitates having access to institutional funding. The welfare of farmers and agricultural productivity are typically restricted by limited financial resources (Shitaye et al., 2024; Khemundu & Majhi, 2026). The limited access to credit and financial services in the rural areas of this region prevents farmers from investing in quality seeds, fertilisers and modern equipment, thereby reducing agricultural productivity and adversely affecting their overall socioeconomic wellbeing (Baliwada et al., 2017; Kumar et al., 2023; Ullah et al., 2024; Hiranya & Joshi, 2025).

METHODOLOGY

The study examined the multidimensional livelihood structure of paddy farmers in Koraput district of Odisha and was purposively selected due to its predominantly tribal population, high dependence on rainfed paddy cultivation and documented livelihood vulnerability despite significant agricultural potential. Out of fourteen blocks in the district, four blocks Jeypore, Koraput, Semiliguda and Lamtaput, were purposively chosen based on their substantial concentration of paddy farmers. Two villages from each block were selected where paddy farming is the primary occupation. From each village, 15 farmers were selected using proportionate random sampling, resulting in a total sample of 120 respondents across eight villages. Primary data were collected in 2025 using a structured interview schedule. Thirteen continuous variables (age, income, landholding, livestock holding, farming experience, social participation, innovativeness and risk orientation) and five categorical variables (education, occupation, family size, family type and housing type) were measured to capture the diverse dimensions of farmers' livelihoods.

Prior to conducting Principal Component Analysis (PCA), the suitability of the dataset was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. The overall KMO value was 0.77 indicating good sample adequacies. Bartlett's test was statistically significant ($\chi^2 = 500.669$, $p < 0.001$), confirming that the correlation matrix was appropriate for factor extraction. These results justified the appropriateness of the proceeding with PCA in the present study. Nominal categorical variables were converted into binary indicator variables using one-hot encoding prior to PCA, ensuring appropriate numerical representation without imposing artificial ordinal assumptions in the analysis. The primary goal of Principal Component Analysis is to minimise the dimensionality of a set of data, especially for data sets with many variables that reside in two-dimensional subspaces (Abdi & Williams, 2010). PCA is used to evaluate a set of data representing observations specified by correlated dependent variables. The goal is to extract meaningful information from the data and display it as a set of new orthogonal variables known as Principal Components (Karamizadeh et al., 2013). Categorical variables were transformed using one-hot encoding, and all variables were standardised prior to analysis to ensure comparability across scales.This technique enhanced the research findings by offering a comprehensive data-driven knowledge of complicated linkages within the dataset (Greenacre et al., 2022).

RESULTS

The socioeconomic profile contained 120 farmer observations and 13 original variables that included both continuous and categorical elements. Continuous measurements were made of age, livestock holding (number of animals), annual income, landholding size, agricultural experience, social participation, innovativeness (4–20 scale), and risk orientation. Five categories–education (ordinal coding 0/1/2, reflecting increasing formal education), occupation (categories 3/4/5, representing distinct occupational groupings), family size (1 = smaller; 2 = larger), family type (1/2, commonly interpreted as nuclear versus joint), and house type (2/3, indicating comparatively different housing quality) were transformed using one-hot encoding prior to multivariate reduction.Following encoding, the analytical matrix contained 14 derived features. The dimensional reduction showed that variation among farmers was primarily shaped by three interconnected dimensions: generational experience, resource endowment and behavioural orientation. Age and farming experience aligned along one dominant axis, separating older and highly experienced farmers from relatively younger and more formally educated farmers. A second major dimension reflected disparities in income, livestock ownership and landholding size, indicating clear inequality in economic positioning within the district. Behavioural attributes such as innovativeness and risk orientation formed an additional axis, suggesting that adaptive capacity and openness to change were distributed independently of resource ownership. The clustering patterns observed in the reduced component space further demonstrated that farmers were stratified into distinct livelihood groupings rather than forming a homogeneous population. These findings established that socio-economic differentiation in Koraput district was structured along identifiable gradients, providing empirical evidence of livelihood heterogeneity among paddy farmers.

Table 1 presented the explained variance and cumulative variance associated with each principal component. PC1 accounted for 0.359 (about 35.9%) of the total variance. Inclusion of PC2 increased the cumulative variance explained to 52.9%. PC3 contributed 0.097, raising the cumulative variance to 0.626 (62.6). Subsequent components contributed progressively smaller proportions of variance: PC4 accounted for 0.083 (70.9% cumulative), PC5 for 0.064 (77.3%) and later components added marginal increments. By the seventh component, cumulative variance reached 0.875 and beyond the eighth component, the increase became minimal, with the cumulative variance approaching 1.000 by the PC14. The Sharp decline in explained variance after the initial components suggested that most of the structural variation among respondents was captured within the first three to five principal components, whereas later components contributed only limited additional explanatory power.

Table 2 presented "Top loadings for the first five principal components". Loadings represented the relative contribution of each original variable to the respective component, with the sign indicating the direction of association and the magnitude reflecting the strength of influence. PC1 was primarily characterised by positive loadings on age (0.44) and farming experience (0.44) and a negative loading on education (-0.42). High score on PC1 were therefore associated with older farmers possessing greater farming experience but lower levels of education, whereas lower PC1 scores corresponded to relatively younger and more educated farmers. PC2 showed that strong positive loadings for income (0.62) and livestock holding (0.59), along with moderate loading for land size (0.28). High score on PC2 were associated with greater income, large landholdings and higher livestock ownership, indicating a resource or wealth dimension. PC3 was defined mainly by positive loadings on risk orientation (0.56) and innovativeness (0.49) with a smaller contribution from age (0.38). Higher PC3 score associated with more risk-oriented and innovative farmers. PC4 exhibited a positive loading on social participation (0.54) and negative loadings on risk orientation (-0.45) and income (-0.45). Higher PC4 score were associated with greater social engagement and comparatively lower income and risk orientation. PC5 was characterised by a strong positive loading on innovativeness (0.64) and negative loadings on land size (-0.55) and social participation (-0.31). Higher PC5 Scores were associated with innovative farmers possessing relatively smaller landholdings and lower levels of social participation (-0.31). Higher PC5 scores were associated with innovative farmers possessing relatively smaller landholdings and lower levels of social participation.

Table 3 presented the mean PC1 and PC2 scores across categorical variables, indicating the positioning of different socio-demographic groups along the first two principal components. PC1 represented the experience–education dimension, while PC2 reflected the resource dimension. For education, categories 0, 1 and 2 recorded mean PC1 scores of 1.79, –0.38 and –2.10 respectively, demonstrating that lower education levels were associated with higher PC1 scores (older and more experienced), whereas higher education levels were associated with negative PC1 scores. Mean PC2 scores across education categories (0.15, –0.04 and 0.17) showed minimal variation, suggesting limited differences in resource endowment by schooling level. Occupational categories (3, 4 and 5) recorded mean PC1 scores of 0.35, –0.71 and –0.27 and mean PC2 scores of 0.15, 0.25 and –0.52 respectively, indicating that category 4 farmers possessed relatively higher resource levels but lower experience scores, while category 5 farmers exhibited

Table 1. Explained variance of principal components

PC	Explained variance	Cumulative variance
PC1	0.359	0.359
PC2	0.170	0.529
PC3	0.097	0.626
PC4	0.083	0.709
PC5	0.064	0.773
PC6	0.054	0.827
PC7	0.048	0.875
PC8	0.038	0.913
PC9	0.027	0.940
PC10	0.017	0.957
PC11	0.016	0.972
PC12	0.013	0.985
PC13	0.009	0.994
PC14	0.006	1.000

Table 2. Top loading for the first five principal components

PC	Dominant variable	Interpretation
PC1	Age (0.44), Farming experience (0.44), Education (-0.42).	Opposes older, experienced farmers against more educated farmers. High PC1 scores correspond to older, less educated farmers with long farming experience.
PC2	Income (0.62), Animals (0.59), Land size (0.28)	Represents the wealth dimension, a higher PC2 score reflects higher income, more livestock and land holding.
PC3	Risk orientation (0.56), Innovativeness (0.49), Age (0.38)	Differentiates risk-oriented, innovative farmers from more conservative ones.
PC4	Social participation (0.54), Risk orientation (-0.54), Income (-0.40)	Contrasts social engagement with risk aversion and income socially active farmers score high, whereas wealthier and more risk-oriented farmers score low
PC5	Innovativeness (0.64), land size (-0.55), social participation (-0.31)	Highlights an innovativeness versus land size axis innovative farmers with smaller holdings and lower social participation have high PC5 scores.

Table 3. Mean PC1 and PC2 scores for categorical variables

Category	Code	Mean PC1	Mean PC2	Interpretation
Education	0,1,2	1.79, -0.38, -2.10	0.15, -0.04, 0.17	Low education (code 0) aligns with higher PC1 (older, experienced); high education (code 2) has strongly negative PC1 scores. PC2 varies little across education levels.
Occupation	3,4,5	0.35, -0.71, -0.27	0.15, - 0.4, -0.17	Category 3 farmers are older and wealthier (positive PCs), category 4 shows the highest wealth but lower experience, category 5has lower wealth (negative PC2)
Size of family	1 (small) 2 (large)	-0.71, 0.38	-0.78, 0.42	Larger families cluster with positive PC1/PC2, implying more resources and experience. Smaller families have negative scores on both axes.
Types of family	1,2	-0.40, 0.05	-0.66, 0.08	Type 2 families (likely joint or extended) have slightly positive scores on both PCs, while type 1 families are negative on both axes.
Types of house	2,3	0.84, -0.84	-0.21, 0.21	Housing quality aligns strongly with PC1: household coded 2 (better house) have high PC1, whereas code 3 (poorer houses) have negative PC1

comparatively lower resource positioning. Family size also showed differentiation, with small families (code 1) recording mean PC1 and PC2 scores of –0.71 and –0.78, whereas large families (code 2) recorded 0.38 and 0.42, suggesting greater experience and resource alignment among larger households. Family type showed modest differences, with type 1 families recording –0.40 (PC1) and –0.66 (PC2), while type 2 families recorded 0.05 and 0.08 respectively. Housing type exhibited clear separation along PC1, with type 2 households recording 0.84 and type 3 households recording –0.84, indicating differentiation along the experience–education dimension; however, PC2 values (–0.21 and 0.21) suggested only marginal variation in resource ownership across housing types. Overall, the categorical groups demonstrated structured alignment along the dominant livelihood dimensions identified in the analysis.

The scree plot showed two key pieces of information for every principal component (PC), Individual explained variance (blue bars) – how much of the total variability each PC captures on its own. Cumulative explained variance (red dashed line) – the running total of variance captured up to that component. From the plot, PC1 accounts for roughly 36% of the variance, and PC2 adds about 17%, meaning the first two components together explain over half the variability in the data. PC3 contributes another ~10%. After PC3, the bars get much smaller, indicating that PCs 4–14 explain progressively less variance. The cumulative curve rises steeply at first and then flattens out; this "elbow" around PC3/PC4 is a common heuristic for selecting how many components to retain.

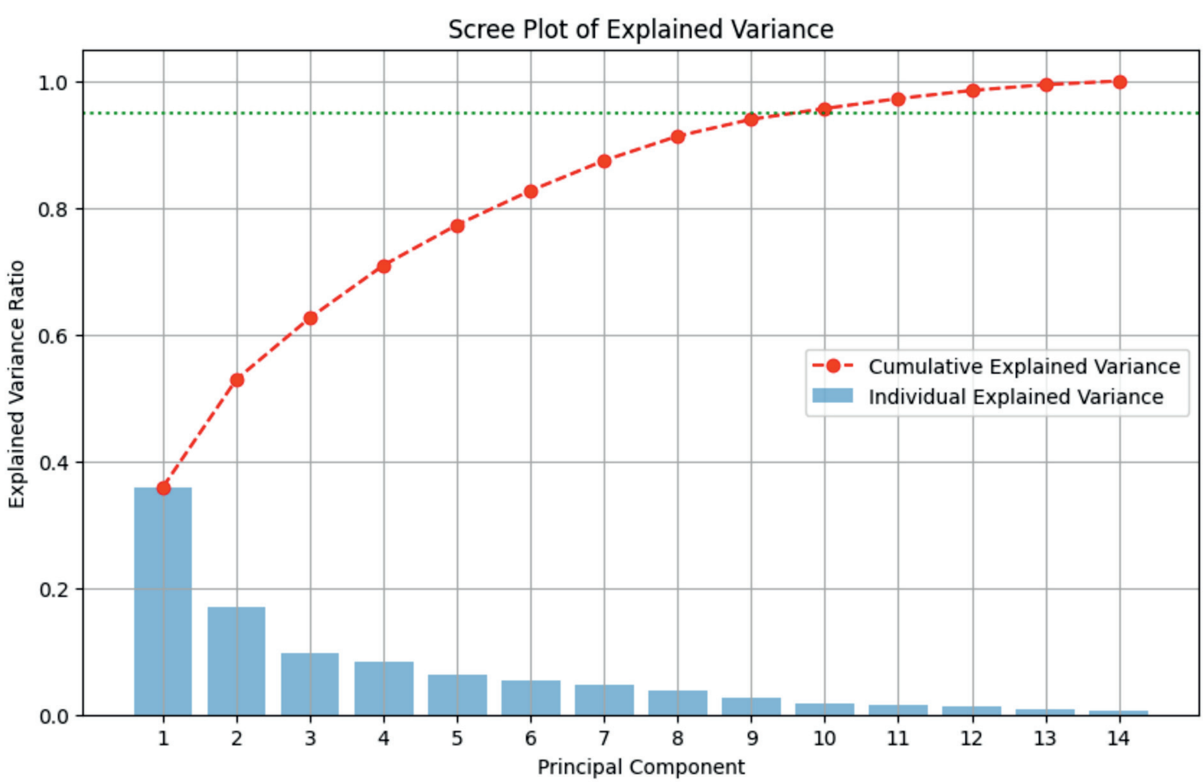

Figure 1. Scree plot of explained variance

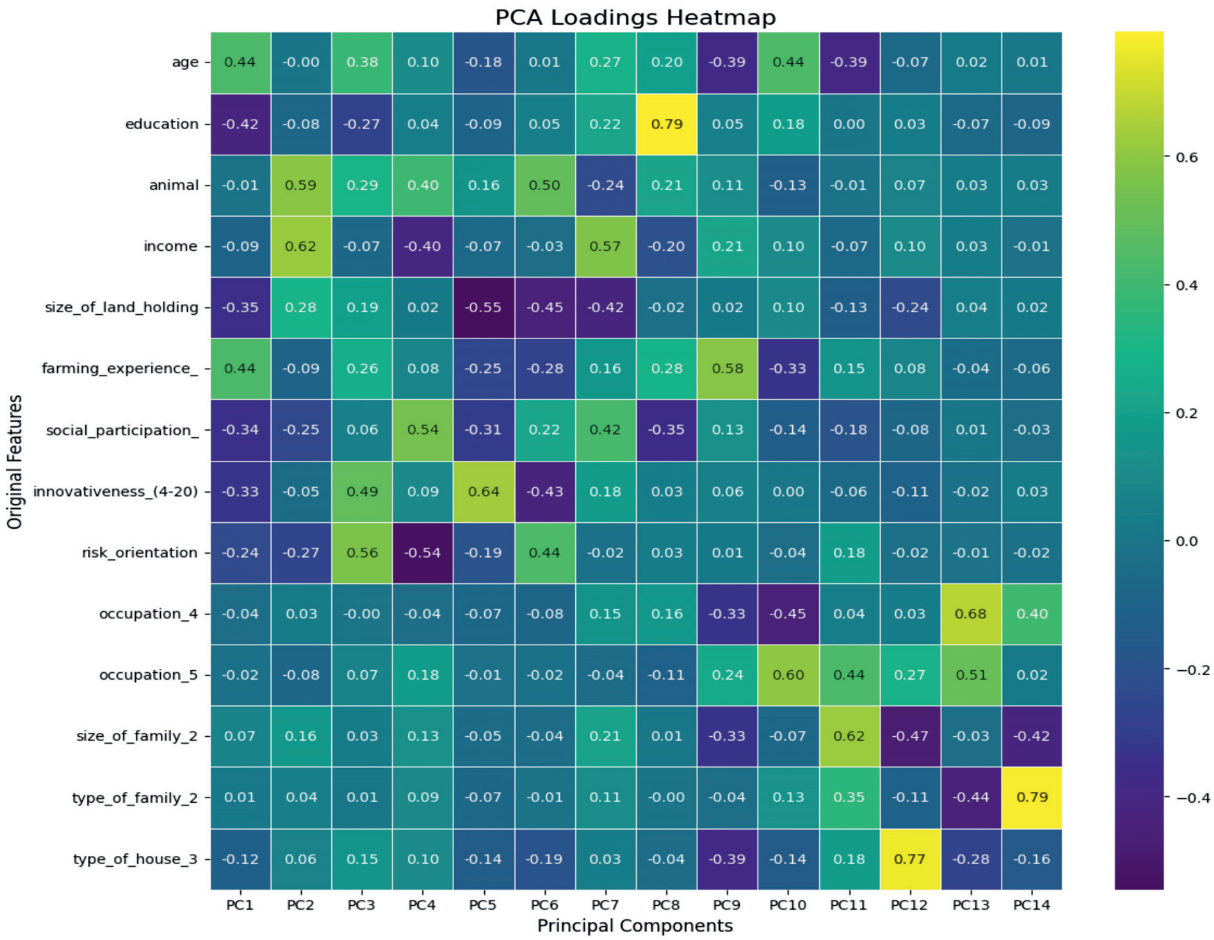

Figure 2. PCA Loadings heat map

By the time ten components are included, the cumulative variance exceeds 95/ %, but most of the structure is already captured in the first few.

The heat map displayed the loadings (weights) of each original variable on each principal component. Rows correspond to the original variables, and columns correspond to PCs. Colour intensity and sign convey the magnitude and direction of each loading (yellow/green for positive, blue for negative). PC1 has strong positive loadings on age and farming experience, and a strong negative loading on education. This confirms that PC1 contrasts older, experienced farmers with those who have more formal education. PC2 is dominated by income and animal, with smaller contributions from size of land holding. These positive loadings indicate that PC2 is essentially a wealth/resource axis.PC3 shows large positive loadings for risk orientation and innovativeness, distinguishing innovative, risk taking farmers from more conservative ones. Later components highlight more specialised patterns: for example, education loads heavily on PC12 (0.79), occupation_4 on PC13 (0.68) and type_of_family_2 on PC14 (0.79). These components capture variations specific to individual categories rather than broad socio economic trends. This heatmap also makes it clear that most categorical dummy variables contribute strongly to later PCs rather than to the first few, which is why the first components are driven largely by continuous socio economic variables.

The biplot overlays the scores of the observations (blue dots) onto the loading vectors (red arrows) for the first two principal components. It allows you to see how individuals cluster in the reduced space and how variables influence those positions. The horizontal axis (PC1) separates individuals by age/experience vs. education. Points to the right have higher age and farming experience and lower education; points to the left are more educated and often have poorer housing conditions (as indicated by the type of house arrow pointing left). The vertical axis (PC2) represents wealth and resources. Points higher up correspond to farmers with greater income, more animals and larger land holdings; points lower down have lower income and fewer resources. The arrows for income and animal are nearly vertical, indicating they load heavily on PC2 and minimally on PC1. The vector directions, arrows pointing in similar directions represent positively correlated variables. For example, income and animal arrows are close together, showing that these measures of wealth tend to increase simultaneously. Arrows pointing in opposite directions, such as age (right) and education (left), reflect negative correlations. Arrows at right angles (e.g., income vs. risk orientation) suggest little or no correlation between those variables in the original data. Most observations cluster around the origin, but there are notable groups: a right-hand cluster (older, less educated, more experienced farmers), an upper cluster (wealthier farmers with high income and livestock), and a lower-left cluster (more educated or smaller farmers with

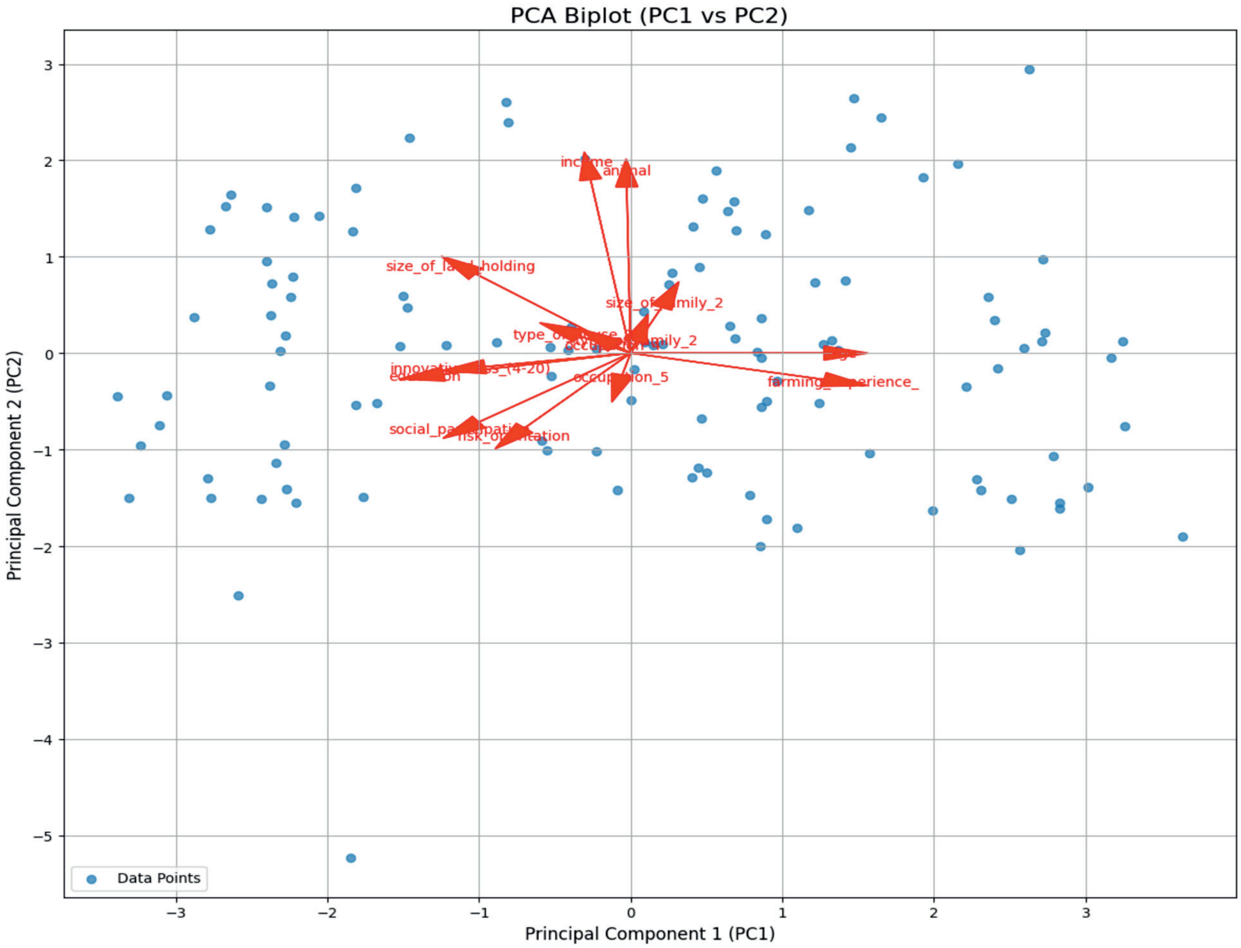

Figure 3. PCA Biplot

lower wealth). Outliers at the far right of the x axis correspond to farmers with very long experience and low formal education.

DISCUSSION

The present study, based on primary data collected from 120 paddy farmers in Koraput district, reveals that livelihood differentiation in this tribal agrarian region is socially structured rather than homogeneous. Although the first two principal components explained 52.9% of total variation, their importance lies in highlighting underlying socio-economic transitions within the district. The experience–education gradient reflects an ongoing generational shift in Koraput's farming communities. Older farmers, characterised by long farming experience but limited formal education, continue to depend largely on indigenous knowledge systems and traditional cultivation practices suited to rainfed conditions. Their decision-making is shaped by risk minimisation and ecological familiarity developed over decades. In contrast, younger farmers with comparatively higher formal education represent an emerging group exposed to modern information sources and institutional extension systems. However, many among them lack sufficient land and livestock assets. This generational divergence suggests a structural imbalance between experiential capital and formal human capital, influencing technology adoption patterns and engagement with government schemes.

The wealth–resource dimension identified through income, landholding and livestock ownership reflects economic stratification within tribal villages. In Koraput's predominantly rainfed and geographically remote blocks, asset ownership directly determines resilience against crop failure, price fluctuation and climatic variability. Farmers with larger landholdings and livestock possess greater livelihood security and diversification capacity, while small and marginal farmers remain vulnerable to indebtedness and seasonal income instability. These disparities are linked to broader structural constraints such as fragmented land inheritance, limited irrigation access and uneven penetration of institutional credit in tribal regions. Behavioural traits such as innovativeness and risk orientation further distinguish farmers beyond material resources. The presence of innovative and risk-taking individuals indicates latent entrepreneurial potential within the community. However, the observed contrast between social participation and economic strength suggests that wealthier or risk-oriented farmers may not necessarily be the most socially integrated. In tribal societies where collective norms, kinship networks and self-help groups influence agricultural decisions, weaker social engagement may restrict the diffusion of new practices. Strengthening farmer groups, cooperatives and village-level institutions therefore becomes critical to transform individual innovation into community-wide adoption. Family structure and housing conditions also reflect embedded socio-cultural realities.

Larger or joint families appear to have relatively stronger livelihood positioning, likely due to shared labour and pooled resources. Nuclear households, particularly younger ones, may face greater production risks and financial pressure. Housing quality acts as a visible indicator of socio-economic status and access to welfare schemes, reflecting uneven developmental outreach across remote villages.

Overall, the findings demonstrate that paddy farmers in Koraput cannot be approached as a uniform extension target group. Livelihood variation is shaped by generational transition, asset distribution and behavioural orientation within a tribal socio-cultural framework. Extension strategies must therefore be stratified and context-sensitive. Older farmers require participatory training that respects indigenous knowledge while introducing gradual technological improvement. Younger but resource-constrained farmers need credit linkage, market integration and entrepreneurship support. Innovative farmers can be mobilised as local opinion leaders to strengthen peer learning and horizontal knowledge exchange. By grounding multivariate evidence in the socio-economic realities of Koraput district, the study underscores the need for socially embedded, inclusive and differentiated extension approaches to strengthen paddy-based livelihoods in tribal regions.

CONCLUSION

The study reveals that paddy farmers in the Koraput district represent a socially and economically diverse community rather than a uniform group. Livelihood patterns are shaped by generational differences, unequal asset ownership and varying behavioural orientations. Older farmers rely strongly on experimental knowledge but have limited formal education, while younger farmers possess greater educational exposure yet often lack adequate productive resources. Economic disparities in landholding, livestock ownership and income significantly influence livelihood security in the districts' rainfed and tribal context. Behavioural traits such as innovativeness and risk orientation further differentiate adaptive capacity among farmers. These findings highlight the need for stratified and context-sensitive extension strategies. Programmes must combine indigenous knowledge strengthening for experienced farmers, institutional credit and market linkage support for resource-poor youth and leadership roles for innovative farmers to promote collective learning. Tailored interventions are essential for improving sustainable paddy-based livelihoods in Koraput and similar tribal regions.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents regarding the study during the course of the data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. 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.

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REFERENCES

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews Computational Statistics*, *2*(4), 433–459. https://doi.org/10.1002/wics.101

Baliwada, H., Sharma, J. P., Burman, R. R., Nain, M. S., Kumar, A., & Venkatesh, P. (2017). Constraints and strategies in scaling up of farmer led innovations. *Journal of Community Mobilization and Sustainable Development, 12*(1), 72-78.

Bharath, M., Sriram, N., Devi, M. N., Padma, S. R., & Selvi, R. G. (2024). Maladies and remedies for KVK trained paddy growers in Cuddalore District of Tamilnadu, India. *Indian Journal of Extension Education*, *60*(4), 140-143. https://doi.org/10.48165/IJEE.2024.604RN4

Birthal, P. S., Roy, D., & Negi, D. S. (2015). Assessing the impact of crop diversification on farm poverty in India. *World Development*, *72*, 70–92. https://doi.org/10.1016/j.worlddev.2015.02.015

Chatterjee, T., Behera, D., Sethy, J., Goswami, S., & Ray, A. (2025). Revolutionising agricultural land suitability and water accessibility assessment using remote sensing: a case study of Jeypore Block, Koraput, Odisha. *Environmental Monitoring and Assessment*, *197*(7), 794.

Greenacre, M., Groenen, P. J. F., Hastie, T., D'Enza, A. I., Markos, A., & Tuzhilina, E. (2022). Principal component analysis. *Nature Reviews Methods Primers*, *2*(1). https://doi.org/10.1038/s43586-022-00184-w

Gual, L., & Das, A. (2025). Have Indigenous regions been left behind? Three decades of development and disparity in Odisha, India. *Social Sciences & Humanities Open*, *12*, 101894. https://doi.org/10.1016/j.ssaho.2025.101894

Hiranya, J., & Joshi, H. G. (2025). Bridging the psychological and policy gaps: Enhancing farmer access to agricultural credit in India. *Acta Psychologica*, *255*, 104890. https://doi.org/10.1016/j.actpsy.2025.104890

Karamizadeh, S., Abdullah, S. M., Manaf, A. A., Zamani, M., & Hooman, A. (2013). An overview of principal component analysis. *Journal of Signal and Information Processing*, *4*(3), 173–175. https://doi.org/10.4236/jsip.2013.43b031

Khemundu, K., & Majhi, N. (2026). The role of tribal women and environmental sustainability in Koraput, Odisha, India. In *Springer studies on populism, identity politics and social justice* (pp. 195–210). https://doi.org/10.1007/978-3-032-02881-5_10

Kumar, S., Nain, M. S., Sangeetha, V., & Satyapriya. (2023). Determinants and constraints for adoption of zero budget natural farming (ZBNF) practices in farmer field school, *Indian Journal of Extension Education, 59*(4), 135-140. https://doi.org/10.48165/IJEE.2023.59427

Manful, J., & Graham-Acquaah, S. (2016). African Rice (*Oryza glaberrima*): A Brief History and Its Growing Importance in Current Rice Breeding Efforts. In *Elsevier eBooks* (pp. 140–146). https://doi.org/10.1016/b978-0-12-394437-5.00016-4

Nayak, M. K. (2025). Social and infrastructural development of tribal population in Koraput district of Odisha: A Case Study. *Shodh Sari-An International Multidisciplinary Journal*, *4*(1), 348–360. https://doi.org/10.59231/sari7799

Pani, P., Patra, A., & Subudhi, R. N. (Eds.). (2025). *Innovative Synergies: Business, Agriculture, Technology and Resource Management for Sustainable Development*. Taylor & Francis.

Rout, D. S., Deb, A., Bhadra, P., & Nandy, A. (2025). Health, food security and livelihood diversification in rural Odisha: A review. *Plant Science Today, 12*(1), 3507. https://doi.org/10.14719/pst.3507

Saha, S., Reddy, M. D., Patra, A., & Suman, S. (2025). A study on socio-economic profile and the knowledge level of paddy farmers in the Gajapati district of Odisha. In *Innovative Synergies* (pp. 109-119). Routledge.

Shitaye, Z., Tadesse, B., & Enkuahone, K. (2024). Determinants of smallholder farmers' choices of agricultural information sources and outlets: Evidence from East Gojjam zone, Amhara, Ethiopia. *Heliyon*, *10*(22), e40344. https://doi.org/10.1016/j.heliyon.2024.e40344

Singh, A., Singh, A., Yadav, B., & Malik, J. S. (2024). Farmers attitude towards organic farming in Uttar Pradesh. *Indian Journal of Extension Education*, *60*(3), 33–36. https://doi.org/10.48165/ijee.2024.60307

Thangjam, B., & Jha, K. K. (2024). Farmers' attitude towards adoption of sustainable agricultural practices: A study in Manipur. *Indian Journal of Extension Education*, *60*(4), 35-39. https://doi.org/10.48165/IJEE.2024.60407 .

Touch, V., Tan, D. K., Cook, B. R., Liu, D. L., Cross, R., Tran, T. A., Utomo, A., Yous, S., Grunbuhel, C., & Cowie, A. (2024). Smallholder farmers' challenges and opportunities: Implications for agricultural production, environment and food security. *Journal of Environmental Management*, *370*, 122536. https://doi.org/10.1016/j.jenvman.2024.122536

Ullah, A., Verner, V., Madaki, M. Y., Adams, F., & Bavorova, M. (2024). Factors influencing informal credit access and utilization among smallholder farmers: insights from mountainous regions of Pakistan. *Agriculture*, *14*(10), 1764. https://doi.org/10.3390/agriculture14101764

Yadav, B., Maurya, A. S., Supriya, Narain, S., & Kumar, A. (2025). Socio-economic determinants of agriculture households in Punjab: A principal component analysis. *Indian Journal of Extension Education*, *62*(1), 41–47. https://doi.org/10.48165/ijee.2026.62107