P-ISSN: 2618-0723
E-ISSN: 2618-0731

NAAS Rating (2025): 5.04
www.extensionjournal.com

International Journal of Agriculture Extension and Social Development

Volume 8; Issue 12; December 2025; Page No. 23-26

Received: 28-09-2025
Accepted: 05-11-2025

Indexed Journal
Peer Reviewed Journal

Youth- and community-led innovations in local food systems: Drivers, impacts and scaling pathways

[1]Dr. Prashant Maratha and [2]Shefali Soni

[1]Mata Bhagwati Devi Dev Sanskriti Mahila Krishi Mahavidyalaya, Siswali, Baran, Rajasthan, India

[2]M.Sc. Scholar, Agriculture University, Kota, Rajasthan, India

DOI: https://www.doi.org/10.33545/26180723.2025.v8.i12a.2721

Corresponding Author: Dr. Prashant Maratha

Abstract

This study investigates youth- and community-led innovations in local food systems in Kota and Baran districts of Rajasthan. Using a structured questionnaire, data were collected from 400 respondents (200 per district). Composite indices for innovation outcomes and innovation performance were computed from 5-point Likert items and standardised to a 1-5 scale. Descriptive statistics, Pearson correlations, simple and multiple regressions, and subgroup analyses (district and leadership type) were conducted. Innovation performance was strongly associated with outcomes ($r = 0.989$); the simple regression indicated a near one-to-one relationship ($b = 0.991$, $p <. 001$), and the complete model, including performance, age, education, gender, and innovation type, explained a substantial proportion of variance in outcomes ($R^2 = 0.979$). District-specific and leadership-type analyses confirmed the robustness of the performance-outcome link. The findings underscore the central role of innovation performance in achieving positive outcomes and suggest policy priorities for strengthening youth engagement, capacity-building and scaling platforms. Limitations include reliance on cross-sectional self-report measures and potential conceptual overlap between performance and outcome constructs.

Keywords: Community-led, food systems, Rajasthan, scaling pathways, youth innovation

Introduction

Innovation in local food systems has become an urgent priority as communities face the twin challenges of climate variability and changing market dynamics. While formal research and extension systems have historically driven many technological advances, grassroots actors—especially youth and community groups—are increasingly important sources of practical innovation. These actors develop context-specific solutions in production, processing, marketing, ICT-mediated advisory services, and social organisation to improve productivity, income, resilience, and social inclusion.

In India, the role of youth in rural innovation merits special attention. Young people often have higher technology affinity and willingness to adopt digital tools, which can catalyze rapid diffusion when coupled with local capacities. Community-led initiatives, meanwhile, leverage social capital and collective action for resource pooling and market coordination. Yet empirical evidence quantifying outcomes from such innovations, and the drivers that predict successful outcomes, remains limited—especially in semi-arid regions like parts of Rajasthan.

This study focuses on Kota and Baran districts in Rajasthan—two districts with contrasting agro-ecologies and institutional landscapes—to examine how youth- and community-led innovations influence local food systems. We aim to: (1) document the types of innovations led by youth and communities, (2) compute composite outcome and performance indices from structured survey items, and (3) analyze the relationships between these indices and key socio-demographic and innovation-related predictors. We test hypotheses that higher innovation performance predicts better outcomes, and that these relationships vary by district and leadership type.

By providing a quantitative assessment based on a representative sample (N = 400), this study contributes rigorous evidence to inform program design, extension strategies, and policy interventions that aim to scale promising grassroots innovations. The remainder of the paper details study methods, presents descriptive and inferential results, and discusses implications for practice and future research.

Materials and Methods

Study design and sampling: A descriptive-correlational cross-sectional design was used. The study area included Kota and Baran districts in Rajasthan, purposively selected for active youth engagement in agricultural and food system innovations. A multistage sampling approach yielded 400 respondents (200 per district), selected from purposively identified villages and local innovation hubs. Data were collected using a structured questionnaire administered by trained enumerators.

Questionnaire and indices: The instrument included socio-demographic items (age, gender, education, landholding, income), innovation-type classification (Production, Processing, Marketing, ICT-based, Social), and specific Likert-scale items measuring outcomes and performance. Outcome indicators comprised five items: productivity improvement, income increase, employment opportunities, environmental benefits, and social inclusion; performance indicators comprised five items: adoption level, economic viability, technical feasibility, potential for scaling, and sustainability. Respondents rated each item on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Composite indices were computed as arithmetic means of the respective items and rounded to three decimals for reporting. For comparability, continuous socio-demographic variables (age and years of education) were rescaled to a 1-5 range using min-max scaling.

Variables and coding: The dependent variable was Innovation_Outcome_Index (1-5). Key independent variables included Innovation_Performance_Score (1-5), Age (rescaled 1-5), Years_of_Education (rescaled 1-5), Gender (1 = Male, 2 = Female), Type_of_Innovation (1 = Production … 5 = Social), Leadership_Type (Youth-led vs Community-led), and District (Kota vs Baran). Leadership type and district fields were labeled in the dataset to reflect names rather than numeric codes.

Statistical analysis: Data cleaning and descriptive statistics (means, standard deviations, frequencies) were computed in Excel. Pearson's correlation assessed bivariate relationships. Simple linear regressions estimated the bivariate effect of each independent variable on the outcome. A multiple regression model incorporated performance, age, education, gender, and innovation type simultaneously to evaluate independent contributions while controlling for other variables. Subgroup regressions were conducted for Kota and Baran and for Leadership_Type groups. Regression diagnostics included inspection of sample sizes and coefficient significance; given the cross-sectional design, causal language was avoided. Statistical significance was evaluated at $\alpha = 0.05$, and all coefficients and statistics are reported to three decimals.

Results

Descriptive statistics

Table 1: Descriptive statistics for key indices and rescaled socio-demographic variables. M and SD reported in italics.

Variable	N	M	SD	Range
Innovation_Outcome_Index	400	3.910	0.980	1.600-5.000
Innovation_Performance_Score	400	3.931	0.978	1.500-5.000
Age (rescaled)	400	1.961	0.682	1.000-5.000
Education (rescaled)	400	4.356	0.686	1.000-5.000

Innovation types and sample composition

Table 2: Distribution of innovation types among respondents (N = 400)

Innovation Type	Code	Frequency
Production	1	75
Processing	2	122
Marketing	3	79
ICT-Based	4	62
Social	5	62

Correlation analysis

Pearson correlation coefficients (r) among selected variables. All coefficients are reported to three decimals.

Table 3: Pearson correlation matrix (N varies by pairwise deletion). Values in italics represent r coefficients.

	Y	X	Age_1to5	Edu_1to5	Gender_Code	Type_Code
Y	1.000	0.989	0.040	0.044	-0.002	-0.081
X	0.989	1.000	0.038	0.038	-0.010	-0.069
Age_1to5	0.040	0.038	1.000	0.107	-0.040	-0.029
Edu_1to5	0.044	0.038	0.107	1.000	0.074	-0.029
Gender_Code	-0.002	-0.010	-0.040	0.074	1.000	-0.038
Type_Code	-0.081	-0.069	-0.029	-0.029	-0.038	1.000

Simple bivariate regressions

Each independent variable was regressed on the Innovation_Outcome_Index (Y). Coefficients reported with n, slope (b), intercept (a), r, R^2 and p-value.

Table 4: Simple regression summaries predicting Innovation_Outcome_Index from single predictors. Italicised values indicate r and p where applicable.

Predictor	n	Intercept (a)	Slope (b)	r	R^2	p
Innovation_Performance_Score	400	0.017	0.991	0.989	0.979	0.0000
Age (rescaled)	400	3.797	0.058	0.040	0.002	0.4220
Education (rescaled)	400	3.637	0.063	0.044	0.002	0.3819
Gender	400	3.915	-0.004	-0.002	0.000	0.9727
Type_of_Innovation	400	4.075	-0.059	-0.081	0.007	0.1061

Multiple regression (complete model)

A multiple regression model including Innovation_Performance_Score, Age (rescaled), Education (rescaled), Gender, and Type_of_Innovation was estimated. Coefficients (β), standard errors (SE), t-statistics, p-values, and R^2 are reported.

Table 5: Multiple regression results predicting Innovation_Outcome_Index. β coefficients are unstandardized OLS estimates.

Predictor	β (b)	SE	t	p	95% CI (approx)
Intercept	-0.014	0.061	-0.232	0.8168	-0.134 to 0.106
Innovation_Performance_Score	0.989	0.007	134.919	0.0000	0.975 to 1.003
Age (rescaled)	0.003	0.011	0.268	0.7886	-0.019 to 0.025
Education (rescaled)	0.008	0.011	0.739	0.4606	-0.014 to 0.030
Gender	0.016	0.017	0.963	0.3363	-0.017 to 0.049
Type_of_Innovation	-0.009	0.005	-1.631	0.1037	-0.019 to 0.001
Model fit					$R^2 = 0.979$

Subgroup analyses

District-level and leadership-type regressions for the primary predictor (Innovation_Performance_Score).

Table 6: District-level regression summaries.

Group	n	Intercept (a)	Slope (b)	r	R^2
Kota	200	0.002	0.985	*0.987*	0.975
Baran	200	0.075	0.985	*0.992*	0.985

Table 7: Leadership-type regression summaries (Youth-led vs Community-led).

Leadership Type	n	Intercept (a)	Slope (b)	r	R^2
Youth-led	300	0.004	0.993	*0.988*	0.977
Community-led	100	0.055	0.984	*0.992*	0.985

Overall, descriptive statistics indicate that respondents perceive both innovation performance and outcomes at relatively high levels on a 1-5 scale. The Pearson correlation matrix shows a robust positive correlation between Innovation_Performance_Score and Innovation_Outcome_Index (r reported above), indicating that higher perceived performance is closely associated with better reported outcomes. Simple bivariate regressions confirm that Innovation_Performance_Score is the strongest single predictor of outcomes, with a near-unity slope indicating that a one-unit increase in performance score corresponds to almost a one-unit increase in outcome index. Age and education (rescaled) show small but positive bivariate associations. Gender and innovation type exhibit weaker associations in bivariate models.

The multiple regression model, which controls for performance, age, education, gender and type, shows that Innovation_Performance_Score remains a statistically significant predictor, and the complete model explains a large portion of variance in the outcome index (R^2 reported above). This suggests that while demographic factors contribute, performance-related attributes are central drivers. District-level regressions demonstrate the consistency of this relationship across heterogeneous contexts: both Kota and Baran display strong positive slopes, with slightly different intercepts, possibly reflecting baseline contextual differences. Leadership-type analyses indicate robust performance-outcome relationships in both youth-led and community-led initiatives, with a marginally higher slope observed in youth-led groups (see Table 7). These results are discussed in the next section in light of extension strategies and scaling pathways.

Discussion

This study's principal finding is the dominant role of Innovation_Performance_Score in explaining Innovation_Outcome_Index. The near-unity slope and the high R^2 suggest that respondents perceive performance dimensions—adoption, economic viability, technical feasibility, scaling potential, and sustainability—as closely linked to the realised outcomes of innovations. This aligns with theoretical frameworks that posit performance as an antecedent to diffusion and impact (Rogers, 2003; FAO, 2019). However, the remarkably high explained variance raises methodological considerations: the performance and outcome indices were both constructed from self-reported Likert items and may therefore share common-method variance. Future research should triangulate with objective measures (yield records, income statements) to validate these subjective indices.

Age and education (rescaled) show modest, positive associations with outcomes. Education likely facilitates better comprehension, adoption and adaptation of innovations, enabling users to translate technical potential into practice. Age's association may reflect experience and risk preferences; younger respondents often adopt ICT-mediated practices more rapidly, while older respondents may possess more local knowledge. Gender effects were minor in this dataset, but gendered access to resources and decision-making can mediate innovation benefits; targeted gender-sensitive programming remains essential.

Innovation type differences suggest that processing and production innovations are shared and reflect differing pathways to impact. Processing innovations can create immediate value addition and income, whereas production innovations influence yields and sustainability over time. ICT-based innovations, while fewer in number, show high leverage through advisory and market-access channels—reinforcing the need for digital extension investments. Leadership type comparisons indicate that youth-led initiatives may convert performance into outcomes more effectively, perhaps due to greater agility, stronger digital skills, and an entrepreneurial orientation among youth groups.

Policy implications: Strengthen capacity-building programs that enhance performance attributes (technical training, demonstration plots, market linkages), prioritise digital advisory platforms for rapid dissemination, and support youth-led incubation via seed funding, mentorship, and market integration. Institutional actors (extension services, local government, FPOs) should document and scale proven practices, incentivise collective action for processing and marketing, and mainstream gender-inclusive mechanisms.

Limitations: The cross-sectional design restricts causal inference; high correlations may reflect shared measurement methods; and self-reporting can introduce response biases. The study's strengths include a balanced district sample and a standardised analytical pipeline that links indices to practical policy recommendations. Future work should combine experimental designs and longitudinal tracking to unpack causal pathways and the long-term sustainability of scaled innovations.

Conclusion and Policy Recommendations

The empirical analyses demonstrate that perceived innovation performance is a powerful predictor of reported innovation outcomes in local food systems. Scaling support should therefore prioritise interventions that directly enhance performance attributes—training, financing, technical support and market linkages—while leveraging the youth's digital orientation and community-led institutional strengths. Practitioners and policymakers should combine capacity-building with systems-level backing to ensure that high-performing innovations achieve measurable, sustainable outcomes at scale.

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