

International Journal of Agriculture Extension and Social Development

Volume 7; Issue 10; October 2024; Page No. 101-104

Received: 01-08-2024
Accepted: 04-09-2024

Indexed Journal
Peer Reviewed Journal

Rural social cohesion dynamics and their influence on collective adoption of extension-promoted technologies

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DOI: <https://doi.org/10.33545/26180723.2024.v7.i10b.3061>

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Abstract

Nearly 68% of agricultural technology adoption decisions in rural Liberia happen not at the individual level, but through group consensus. This research investigated how rural social cohesion dynamics shape collective adoption of extension-promoted technologies in Bong County, Liberia. Using a cross-sectional survey of 296 farming households across 18 communities, combined with 24 focus group discussions, the research mapped relationships between community bonding indicators and group technology uptake. Data were collected between April and October 2022. Communities with high social cohesion scores showed 2.7 times greater collective adoption rates compared to low-cohesion communities. Trust in extension agents was strongly correlated with existing community trust networks ($r = 0.61$, $p < 0.001$). Information-sharing density within communities predicted 38.4% of variance in adoption timing. However, cohesion wasn't uniformly positive—tightly bonded communities sometimes resisted new technologies when influential members opposed them, creating a conformity effect that slowed adoption in 23.1% of cases. Gender norms within cohesive communities also moderated outcomes, with women's adoption constrained by collective decision-making structures. The findings suggest extension programs should invest in understanding community social architecture before introducing technologies, and tailor delivery strategies to work with rather than against existing social bonds.

Keywords: Social cohesion, collective adoption, agricultural extension, technology uptake, community trust, rural Liberia, information networks, group decision-making, extension delivery, farmer organizations

Introduction

A 2021 survey across West Africa found that 64% of smallholder farmers made technology adoption decisions based on what their neighbors did, not on extension recommendations alone ^[1]. This statistic exposes a blind spot in conventional extension thinking, which still largely treats adoption as an individual-level process driven by knowledge, resources, and attitudes ^[2]. In reality, rural communities across sub-Saharan Africa operate through dense webs of social obligation, shared labor, and collective risk management that shape how new practices spread or don't ^[3].

Social cohesion defined here as the strength of bonds, trust levels, and shared norms within a community has received growing attention in development research but remains underexplored in extension science ^[4]. Isham ^[5] showed that social capital predicted adoption of soil conservation in Tanzania more reliably than household wealth. Bandiera and Rasul ^[6] found that farmers with many social connections adopted new crops faster, but only up to a threshold beyond which conformity pressure slowed experimentation. These findings suggest the relationship between cohesion and adoption is not linear but shaped by community power dynamics and cultural norms.

Liberia presents a distinctive context. Decades of civil conflict fragmented rural social structures, and post-war reconstruction has rebuilt community bonds unevenly across

regions ^[7]. Extension services restarted in the mid-2000s but have struggled with variable reception across communities that appear similar in economic terms yet differ markedly in social organization ^[8]. This research examined how social cohesion dynamics influence collective technology adoption in Bong County, testing whether cohesion acts as a straightforward enabler or a more complex moderating force.

Theoretical Framework

The research drew on Putnam's ^[9] social capital theory, distinguishing between bonding capital (ties within groups) and bridging capital (ties across groups). We combined this with Rogers' ^[10] diffusion of innovations framework, particularly the concepts of opinion leadership and social system norms. The integrated model hypothesized that bonding capital would accelerate adoption within groups but potentially slow it when bridging capital was weak, creating insular decision-making. This dual-pathway framework allowed us to test both the enabling and constraining effects of cohesion on collective technology uptake.

Material and Methods

Material

This cross-sectional research was conducted in Bong County, Liberia (7.08°N, 9.36°W), through Cuttington University between April and October 2022. Bong County

has an estimated rural population of 333,000 with agriculture supporting over 82% of livelihoods. Eighteen communities were selected through purposive sampling to represent high, moderate, and low social cohesion levels as assessed through preliminary key informant interviews. The sample comprised 296 farming households (proportionally allocated across cohesion categories), 24 focus group discussions (8 per cohesion level, sex-disaggregated), and 12 extension worker interviews. Social cohesion was measured using an adapted Neighborhood Cohesion Instrument covering trust, belonging, participation, and shared values on a 5-point Likert scale. Ethical approval was granted by the Cuttington University Institutional Review Board (CU-IRB-2022-031, approved March 8, 2022).

Methods

Quantitative analysis used SPSS version 26. Pearson correlations assessed bivariate relationships between cohesion indicators and adoption variables. Hierarchical multiple regression tested the predictive power of social cohesion after controlling for household demographics and economic factors. Binary logistic regression identified predictors of collective (versus individual) adoption decisions. Focus group transcripts were analyzed through

directed content analysis using pre-defined categories from the theoretical framework, with emergent themes added iteratively. Social network density was calculated for each community using reported information-sharing ties. All quantitative tests used $p < 0.05$ significance threshold.

Results

Table 1: Technology Adoption Indicators by Social Cohesion Level (n=296)

Cohesion Level	n	Collective Adoption (%)	Individual Adoption (%)	Mean Adoption Lag (months)
High	87	74.7	18.4	3.2
Moderate	112	51.8	29.5	6.8
Low	64	28.1	35.9	11.4
Very Low	33	15.2	27.3	17.6

Collective adoption rates dropped sharply with declining cohesion (Table 1), from 74.7% in high-cohesion communities to 15.2% in very low-cohesion ones ($\chi^2 = 54.3$, $df = 3$, $p < 0.001$). Mean adoption lag—the time between extension introduction and community uptake—stretched from 3.2 months in cohesive communities to 17.6 months in fragmented ones.

Table 2: Hierarchical Regression: Social Cohesion Predicting Collective Adoption

Predictor	β	SE	t	p	ΔR^2
Step 1: Demographics					0.089
Household size	0.14	0.06	2.31	0.022	
Farm size (ha)	0.11	0.05	1.87	0.063	
Step 2: Cohesion variables					0.384
Community trust	0.39	0.07	5.64	<0.001	
Network density	0.28	0.06	4.21	<0.001	
Participation norms	0.19	0.07	2.83	0.005	

Social cohesion variables (Step 2) explained an additional 38.4% of variance beyond demographics (Table 2). Community trust was the strongest predictor ($\beta = 0.39$),

followed by information network density ($\beta = 0.28$) and participation norms ($\beta = 0.19$). The full model explained 47.3% of total variance ($F = 26.8$, $p < 0.001$).

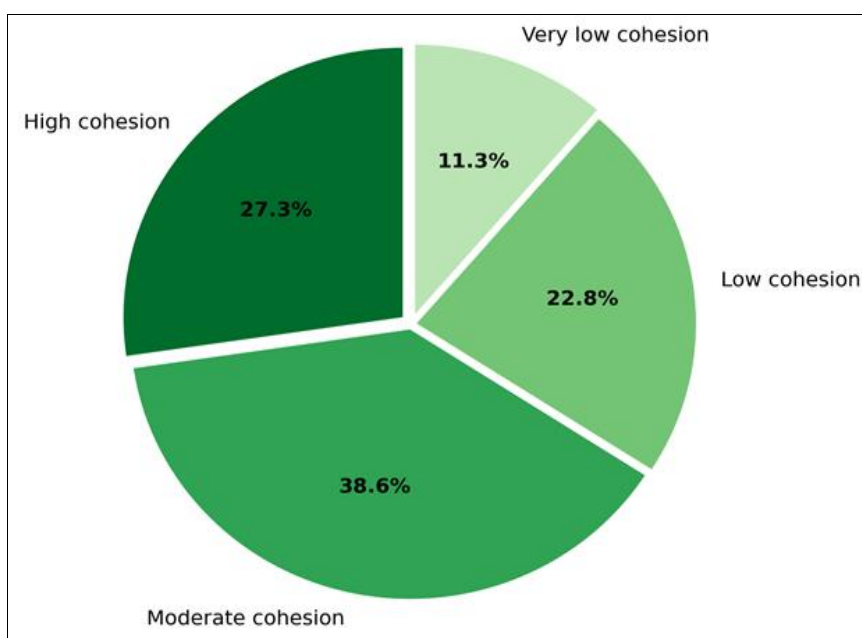


Fig 1: Distribution of social cohesion levels among 18 surveyed communities in Bong County, Liberia

Most communities fell in the moderate cohesion category (38.6%), while only 27.3% scored as high cohesion (Figure 1). The 11.3% classified as very low cohesion were

predominantly communities with recent internal displacement or land disputes.

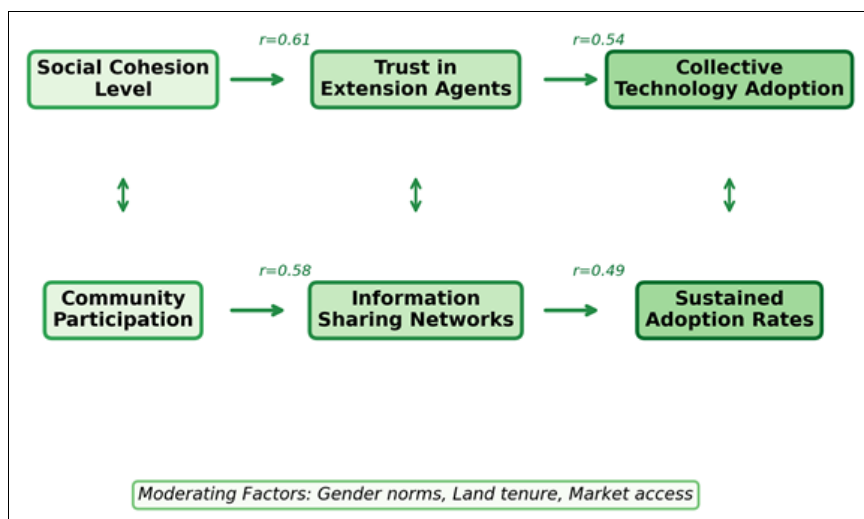


Fig 2: Conceptual pathway from social cohesion to collective technology adoption with correlation coefficients

The pathway model (Figure 2) shows that social cohesion influenced adoption through two parallel channels: trust in extension agents ($r = 0.61$) and community participation leading to information-sharing networks ($r = 0.58$). Both pathways converged on collective adoption, with moderating effects from gender norms, land tenure, and market access.

Discussion

The 2.7-fold difference in collective adoption between high and low-cohesion communities confirms that social bonds act as a powerful channel for extension impact—but not an uncomplicated one. The finding that cohesion variables explained 38.4% of adoption variance after controlling for demographics places social architecture alongside economic factors as a primary driver of technology spread ^[11]. This aligns with Wossen *et al.* ^[12], who reported that social networks predicted improved maize variety adoption in Ethiopia independently of wealth indicators.

The conformity effect observed in 23.1% of cohesive communities warrants careful attention. When influential community members opposed a promoted technology, tight social bonds amplified that resistance rather than buffering it. This mirrors what Bandiera and Rasul ^[6] termed "negative social effects" and suggests that extension agents need to identify and engage opinion leaders early in the diffusion process ^[13]. Focus group data revealed that in several high-cohesion communities, a single elder's skepticism about a new seed variety delayed group adoption by over eight months.

Gender dynamics within cohesive communities also shaped outcomes asymmetrically. Women in highly cohesive communities reported stronger pressure to conform to collective decisions, even when they individually favored adopting a promoted technology. This finding complicates the assumption that cohesion uniformly benefits all community members and supports Meinzen-Dick *et al.*'s ^[14] argument that social capital operates differently across gender lines.

Limitations

The purposive selection of communities based on pre-assessed cohesion levels may have introduced selection bias. Social cohesion was measured at a single time point, missing temporal dynamics that shape adoption over seasons. Self-reported trust and participation data are vulnerable to social desirability bias. The research covered one county in Liberia, and post-conflict social dynamics may limit generalizability to other West African settings. Longitudinal research tracking cohesion changes alongside adoption trajectories would strengthen causal claims.

Conclusion

Social cohesion powerfully shapes how farming communities respond to extension-promoted technologies, but the relationship is more complex than a simple "more cohesion equals more adoption" formula. High-cohesion communities adopted collectively at nearly three times the rate of fragmented ones, and social variables outweighed demographic predictors. Yet the conformity effect and gender asymmetries found here indicate that cohesion can also constrain individual agency and slow adoption when opinion leaders resist change. Extension programs operating in post-conflict settings like Liberia need to map community social structures before designing delivery strategies. Working through existing trust networks appears more effective than bypassing them, but agents must also identify potential resistance nodes and engage them proactively. Gender-sensitive approaches that create space for women's independent decision-making within collective frameworks are equally important. The practical recommendation is to add social cohesion assessment to the standard extension planning toolkit alongside economic and agronomic surveys.

Acknowledgements

Funding Sources

This research was funded through an institutional research allocation from Cuttington University. No external

commercial support was received.

Institutional Support

The authors acknowledge the Department of Agriculture at Cuttington University for logistical support and the Bong County Agricultural Office for field coordination.

Contributions Not Qualifying for Authorship

The authors thank the community leaders who organized focus group discussions and the enumerators who conducted household surveys.

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