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Social learning theory applications in understanding technology diffusion through farming communities

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Abstract

While Rogers diffusion of innovations framework has dominated agricultural extension research for decades, an alternative perspective rooted in Bandura social learning theory offers a fundamentally different explanation of how farming technologies spread through communities. This research applied social learning theory to examine technology diffusion pathways among 312 smallholder farmers across four agricultural districts in Mauritius. A cross-sectional survey combined with social network analysis was conducted between March 2021 and February 2022. Results showed that farmer-to-farmer observation was the primary learning pathway for 34.7% of respondents, exceeding formal extension contacts (23.8%). Observational learning from trusted peers predicted technology adoption more strongly ($\beta = 0.42$, $p < 0.001$) than information exposure alone ($\beta = 0.19$, $p = 0.014$). Social network centrality moderated this relationship, with well-connected farmers serving as amplifiers of observational learning effects. These findings suggest extension strategies should prioritize creating observable demonstration opportunities within existing social networks rather than relying solely on information dissemination.

Keywords: Social learning theory, technology diffusion, observational learning, farming communities, agricultural innovation, Bandura, social networks, extension strategies, Mauritius, smallholder agriculture

Introduction

When a farmer in Pamplemousses district watches a neighbor successfully harvest drip-irrigated tomatoes, something far more complex occurs than simple information transfer. The observer processes visual cues about technique, evaluates outcomes against personal expectations, and draws motivational conclusions about whether the effort is worth attempting. This sequence, formalized by Bandura ^[1] as the four sub-processes of observational learning, captures a dimension of technology diffusion that the dominant diffusion-of-innovations framework largely overlooks.

Rogers ^[2] model treats adoption as primarily an information-processing sequence, positioning social influence mainly as a channel through which information flows. Bandura social learning theory ^[1] shifts attention to the social context itself as the learning environment, arguing that behavior is shaped through observation of models, vicarious reinforcement, and self-efficacy beliefs formed through social comparison ^[3]. Despite theoretical complementarity, agricultural extension research has made surprisingly little use of social learning theory. This research applied Bandura framework to examine how Mauritian farmers acquire technologies through social learning processes, testing whether observational learning predicts adoption independently of formal information exposure.

Conceptual Framework

The research integrated Bandura four sub-processes of observational learning with social network theory. Attention

was operationalized as observation frequency of peer practices; retention through knowledge recall accuracy; reproduction through trial behaviors; motivation through outcome expectations and self-efficacy scales ^[4]. Social network centrality was hypothesized to moderate the strength of observational learning effects ^[5].

Materials and Methods

Materials

The research was conducted across four agricultural districts in Mauritius: Pamplemousses, Flacq, Grand Port, and Savanne, between March 2021 and February 2022. The institutional base was the Department of Agricultural Sciences, University of Mauritius, Reduit. Materials included a structured survey instrument with 46 items measuring social learning processes, technology adoption behavior, social network characteristics, and demographic variables (Cronbach alpha = 0.85). Social network data were collected using a name-generator approach where each respondent identified up to five farmers from whom they regularly sought agricultural advice. Ethical approval was obtained from the University of Mauritius Research Ethics Committee (Protocol UoM/REC/2020-112, approved January 2021).

Methods

A cross-sectional survey was administered to 312 smallholder farmers selected through stratified random sampling. Social network analysis used UCINET software to calculate degree centrality, betweenness centrality, and

clustering coefficients. Quantitative analysis included Pearson correlations, hierarchical multiple regression testing independent effects of information exposure and observational learning with network centrality as moderator [6], and structural equation modeling of the full conceptual model [7].

Results

Table 1: Respondent characteristics and social learning pathway prevalence (n = 312)

Characteristic	Category	n	%
Primary learning pathway	Peer observation	108	34.7
	Extension demo	74	23.8
	Group discussion	57	18.4
	Media (radio/TV)	43	13.6
	Self-experiment	30	9.5
Mean farm size (hectares)			1.4 (SD 0.8)
Mean farming experience (years)			14.7 (SD 8.3)
Mean network degree centrality			4.2 (SD 2.1)
Technologies adopted (last 3 yr)			2.8 (SD 1.6)

Farmer-to-farmer observation was the most common primary learning pathway (34.7%), followed by extension

demonstrations (23.8%). Respondents had moderate farming experience (mean 14.7 years) and were connected to an average of 4.2 other farmers in their advice-seeking networks.

Table 2: Hierarchical regression predicting technology adoption from information exposure and observational learning (n = 312)

Predictor	Beta	SE	t	p-value
Step 1: Farm size	0.16	0.06	2.67	0.008
Step 1: Farming experience	0.12	0.05	2.24	0.026
Step 2: Information exposure	0.19	0.06	3.17	0.002
Step 2: Observational learning	0.42	0.07	6.14	<0.001
Step 3: Network centrality (mod.)	0.21	0.06	3.42	0.001
Step 3: Obs. learning x Centrality	0.17	0.05	3.18	0.002

The final model explained 43.8% of variance in technology adoption. Observational learning was the strongest predictor (beta = 0.42), more than twice the effect of information exposure (beta = 0.19). The significant interaction term (beta = 0.17, p = 0.002) confirmed that social network centrality amplified the effect of observational learning on adoption.

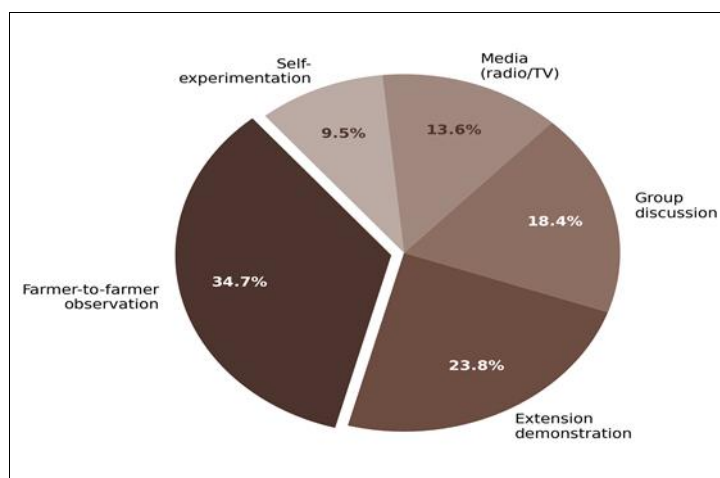


Fig 1: Distribution of primary learning pathways for agricultural technology acquisition (n = 312)

Peer observation dominated, accounting for over one-third of primary pathways. Combined with group discussion,

social learning mechanisms account for 53.1% of all pathways, compared to 23.8% for formal extension.

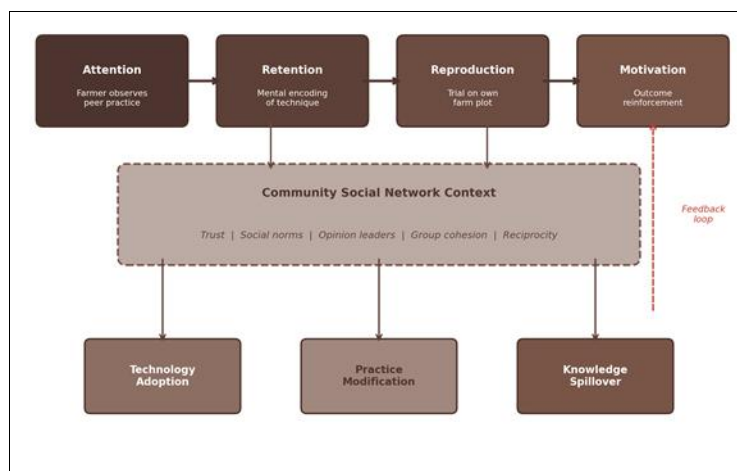


Fig 2: Social learning-based technology diffusion model showing Bandura four processes embedded in community social networks

The model shows how attention, retention, reproduction, and motivation processes operate within community social networks. Trust, social norms, and opinion leader influence moderate the translation of observational learning into adoption, practice modification, and knowledge spillover. The feedback loop reflects the reinforcement cycle sustaining or extinguishing adoption behavior.

Comprehensive Interpretation

Survey and network data converge on a consistent conclusion: technology diffusion in Mauritian farming communities operates substantially through social learning mechanisms beyond information transfer. Farmers observe peers, evaluate outcomes vicariously, and calibrate self-efficacy based on perceived similarity to successful adopters.

Discussion

The finding that observational learning predicted adoption more strongly than information exposure challenges the assumption that providing information is the primary bottleneck to technology uptake^[8]. Bandura theory predicts this: humans learn complex behaviors more effectively through observation because it provides both procedural knowledge and motivational reinforcement simultaneously^[9]. Mauritian data confirm that farmers who watched trusted peers succeed were significantly more likely to attempt a technology than those who only received information^[10]. The moderating role of network centrality has practical implications. Well-connected farmers amplified observational learning effects, acting as nodes through which demonstrations became visible to larger network portions^[11]. This aligns with opinion leadership research^[12] but adds the social learning mechanism: leaders matter not because they provide information but because they serve as observable models whose behavior carries credibility for network peers.

Policy Recommendations

Extension programs should invest in creating structured demonstration opportunities within existing farmer social networks rather than relying primarily on information dissemination. Identifying and supporting well-connected farmers as visible adopters can leverage social learning mechanisms to accelerate diffusion. Training extension agents in social network mapping techniques would enable more strategic placement of demonstration sites and model farmers within communities where observational learning effects are maximized.

Limitations

The cross-sectional design cannot establish causal direction between observational learning and adoption. Self-reported learning pathways are subject to recall bias. Social network data captured only advice-seeking ties, potentially missing other relationship types relevant to technology diffusion. The small island context of Mauritius may limit generalizability to larger continental farming systems with more dispersed social networks.

Conclusion

This research demonstrated that social learning theory

provides a valuable complementary framework to the dominant diffusion-of-innovations model for understanding agricultural technology spread. Observational learning from trusted peers was the strongest predictor of technology adoption among Mauritian farmers, exceeding the effect of formal information exposure. Social network centrality amplified these effects, with well-connected farmers serving as learning models whose adoption behavior influenced broader community uptake. Extension programs that deliberately create conditions for observational learning within existing social networks are likely to achieve stronger diffusion outcomes than those relying primarily on information transfer.

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