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Revisiting Everett M. Rogers: A Machine Learning–Enabled Systematic Review of Technology Adoption in Modern Agriculture

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Abstract

Agricultural innovation is pivotal to meeting global food, climate, and livelihood challenges. This study systematically reviews publications from 2021 to 2025 on agricultural technology adoption. We combine Everett Rogers's diffusion of innovation theory with a supervised machine learning technique: Random Forest (RF), an ensemble tree-based method within the broader AI toolkit, to identify key factors that influence adoption outcomes across 571 cases from 531 publications. Our stepwise approach integrates systematic bibliometric searches, rigorous textual coding and numerical conversion, and RF modeling to synthesize diverse empirical evidence into actionable, data-driven guidance. The RF model, which demonstrates good predictive performance, highlights extension access, climate risk awareness, and perceived relative advantage (along with perceived simplicity and training participation) as the most influential predictors of adoption decisions. Education, or more broadly, innovation literacy, emerges as essential in specific local contexts but less influential across all cases, while peer networks exert moderate, context-dependent effects. These findings suggest that extension messages and programs should emphasize clear, observable benefits, manageable complexity, and climate-related risk information that directly address farmers' needs and concerns. Overall, this integrated methodological approach provides robust and nuanced insights, offering practical guidance for agricultural development policy, extension strategies, and future research.

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Introduction and Problem Statement

Agricultural technologies continuously evolve to adapt to an ever-changing global landscape. Norman E. Borlaug, the father of the first Green Revolution, significantly enhanced global food security from the mid-1960s to the 2000s by developing high-yield hybrid seeds (Wollenweber et al., 2005).

This first Green Revolution relied on genetically improved crop varieties and intensive chemicals optimized for fertile soils. Now, modern agricultural innovations, often referred to as the second Green Revolution, underscore the critical need for crop varieties that produce higher yields in infertile soils, particularly for farmers who utilize fertilizers precisely, face scarcer natural resources, and contend with climate variability (Lynch, 2007; The Economist, 2014). Modern agriculture faces considerable challenges in sustainably feeding a constantly expanding global population, projected to grow from approximately 6 billion in 2000 to over 10 billion by 2050 (Armanda et al., 2019).

Different regional and local conditions call for the second Green Revolution that gives attention to multi-disciplinary scholars and various stakeholders. Rogers (2003) emphasizes the need for agricultural innovations tailored to diverse local contexts, moving beyond previous models that acknowledge their limitations and necessitate broader conceptions. Diffusion researchers demonstrate that a single innovation can yield markedly different adoption trajectories across farming communities, underscoring how locally contingent social, economic, and environmental conditions shape both producer practices and the downstream experiences of consumers as climate pressures alter staple crops (Pugh et al., 2016; The Economist, 2022). Diffusion researchers identify both successes and failures of the same innovation across different farming communities, connecting producers and consumers who may soon experience shifts in staple crops due to various climate conditions (Pugh et al., 2016; The Economist, 2022). Since farming is inherently linked to broader ecosystem processes, understanding innovation diffusion requires addressing what innovation, for whom, where, when, and how it should be introduced for successful adoption (Ahn et al., 2023).

Theoretical and Conceptual Framework

Everett Rogers's diffusion of innovation theory guides this study, helping explain how the adoption of new practices is influenced by interconnected factors such as policy, social status, and risk awareness within social systems (Rogers, 2003). Innovations gain traction when they are easily observable, offer clear benefits (relative advantage), can be tested on a small scale (trialability), are perceived as simple rather than complex to use (low complexity/high simplicity), and align effectively with existing practices and needs (compatibility).

The effectiveness of agricultural technology adoption is further shaped by context-specific socio-economic, cultural, and policy conditions (Rodenburg et al., 2020; Ruzzante et al., 2021). Access to extension services and training often increases the likelihood of adoption, although its effects vary widely across local contexts, resource availability, and risk perceptions (Jellason et al., 2021; Njuki et al., 2022). These variations highlight the need for context-specific approaches that take into account differential access to resources, local constraints, and varying risk awareness among farmers. Sustainable agricultural transitions, therefore, require coordinated, inclusive strategies that leverage communication networks, peer influence, and the inherent attributes of innovations, i.e., core elements of Rogers's framework (Duncan et al., 2021; Lemay & Boggs, 2024; Messéan et al., 2021; Y. Wang et al., 2024).

Across contemporary agricultural systems, the same innovation can follow markedly different adoption trajectories depending on local context, institutional support, and how farmers perceive its attributes. Conservation agriculture, for example, remains below one percent nationally in parts of India, yet reaches majority adoption in project-supported districts of Malawi, Zambia, and Zimbabwe, where farmers have sustained exposure, reliable access to inputs, and visible peer demonstrations (Karki et al., 2024; Ngoma et al., 2024). Similar contrasts emerge for agroforestry and crop diversification: adoption approaches universality in some small-island and Seychelles settings but plateaus at around half or far less in comparable Ethiopian and Indian regions facing similar climate pressures (Etongo et al., 2023; Sisay et al., 2023; Tanti & Jena, 2023). Seed-based innovations and information or decision-support tools show equally heterogeneous patterns. Uptake of drought-tolerant varieties and climate information services remains modest in Ethiopian contexts (Sisay et al., 2023), rises substantially for hybrid maize and rice varieties and climate services in parts of India (Tripathi et al., 2023), and diverges sharply for Integrated Pest Management between Ethiopian smallholders and China's more commercially organized horticultural systems (J. Wang et al., 2024). Even in high-income agricultural systems, diffusion gradients persist: cover crops occupy only a minority of sampled fields in the U.S. Midwest, while digital and precision livestock technologies continue to sit in early adoption stages despite growing interest (Akinyemi et al., 2025; Coon et al., 2025; Guo et al., 2023).

Building on this framework and these patterns, this study addresses gaps in current research by identifying critical factors and predictors that influence the adoption of diverse agricultural technologies in recent empirical publications (2021–2025). We apply a novel methodological approach that combines systematic literature review, rigorous textual coding and numeric conversion, and Random Forest (RF) machine learning analyses. Beyond traditional regression-based meta-analyses, machine learning methods such as RF provide AI-aligned tools for exploring complex, nonlinear interactions among adoption determinants. While RF is not a form of generative AI, it sits within the predictive AI and data science toolbox as a supervised ensemble learning method, in the context of digital agriculture, where farmers and extension systems increasingly rely on data-rich decision-support tools. Such models can highlight which combinations of Rogers-style attributes and contextual factors are most predictive of adoption.

Purpose

The following research questions operationalize the purpose of this study and structure the inquiry.

1. Which factors (e.g., extension access, training participation, perceived complexity, policy support, climate risk awareness) most significantly predict the adoption (or low adoption) of agricultural technologies across different regions?
2. How do context-specific socio-economic and cultural environments influence agricultural innovations' relative advantage, compatibility, trialability, and observability?
3. How do peer networks and educational levels facilitate or hinder adoption?

Methods

The initial literature search employed systematic Boolean queries on the Web of Science (WoS) and Scopus to comprehensively identify publications related to agricultural technology adoption. Separate searches for both databases targeted articles from 2021 to 2025, integrating terms related to technology adoption, innovation diffusion, agricultural practices, Rogers's diffusion theory constructs (e.g., relative advantage, compatibility), advanced technologies (e.g., AI, IoT, CRISPR, conservation agriculture), adoption outcomes (e.g., success, barriers), and geographical regions.

A broader subsequent search for the same period captured recent advancements in precision agriculture, digital technologies, biotechnology, and innovation diffusion across global regions, i.e., North America, Europe, Asia, Africa, Latin America, and Oceania. This broader query incorporated extensive keywords, including precision agriculture, smart farming, regenerative agriculture, biotechnological innovations, and extension networks, resulting in a more robust dataset. Overall, after a detailed review, we retrieved 1,342 publications, which yielded a refined dataset of 571 cases from 531 publications for thorough coding and analysis. R programming (version 4.2.3) within RStudio visualizes a world map showing countries by frequency and a word cloud displaying agricultural technologies. For the word-cloud visualization, we converted all innovation-type labels to lowercase. We removed both standard English stopwords and generic domain terms (e.g., innovation/innovations, agriculture/agricultural, technology/technologies, product/production, practices, systems, crop/crops, climate, use, farming, application/applications) so that the plot would emphasize substantive innovation categories rather than broad descriptors.

For these 571 cases, we employed RF, an ensemble decision-tree method, using Stata 19’s integrated H2O machine learning platform (StataCorp, 2025). RF builds many decision trees on bootstrapped samples of the data, with each tree using a random subset of predictors at each split. Predictions are then aggregated (by majority vote), which typically improves predictive performance and reduces overfitting compared with a single decision tree (Breiman, 2001). We selected RF over a single decision tree because individual trees can be unstable and sensitive to small changes in the data. In contrast, the ensemble approach yields more robust and generalizable estimates of variable importance in heterogeneous, multi-country adoption studies. However, RF has limitations: it requires a sufficiently large sample for bootstrapping, offers less straightforward interpretability than a single tree, and its performance depends on tuning hyperparameters (e.g., number of trees, tree depth, and mtry). We address interpretability by using SHAP values and permutation-based variable importance to relate RF results to Rogers's diffusion constructs.

We evaluated Random Forest performance using 5-fold cross-validation, summarizing generalization error with the model's mean class error (MCR), that is, the average misclassification rate across folds. This internal validation design eliminates the need for a separate holdout set, allowing us to assess model stability and predictive performance while making efficient use of all available cases. Model performance was summarized using MCR, a confusion matrix reporting counts of correct and incorrect classifications, for each adoption category, as well as global discrimination metrics: the Area Under the Precision–Recall Curve (AUCPR) and the Area Under the ROC Curve (AUC).

For the Random Forest analysis, we collapsed the original outcome categories into a binary measure of adoption. Studies were coded as Adopted (Yes/High) when uptake was ≥ 40% or described with strong positive diffusion terms (e.g., "widely adopted," "diffused rapidly," "high adoption"). Studies were coded as 'No/Partial adoption' when uptake was ≤ 39% or described as low, limited, discontinued, or rejected. When exact percentages were not reported, we relied on these textual descriptors as proxies (Table 1). We referred to high-uptake cases as "Adopted (Yes/High)" and low-uptake or discontinued cases as "No/Partial adoption," rather than using terms like "success" or "failure." Cases classified as Neutral or Inconclusive (e.g., pilots, reviews, or studies without clear adoption information) were excluded from the RF model but retained in the descriptive summaries.

Table 1
Target/Outcome Coding Scheme

Outcome	Proxy Terms	Interpretation
Success / Adopted	“uptake clearly,” “partial/high,” “widely adopted,” “scaling,” “positive adoption,” “increased uptake,” “positive impact,” “diffused rapidly,” “well integrated,” “adoption rate high,” “extension success.”	Suggests relative advantage and compatibility
Failure / Partial	“low uptake,” “partial/low,” “barriers,” “rejected,” “unsuccessful,” “limited diffusion,” “failed trial,” “lack of adoption,” “no/discontinued,” “resistance,” “abandonment,” “technology fatigue.”	Suggests poor compatibility, high complexity, or failed policy alignment
Neutral / Inconclusive / Dropped cases	“pilot study,” “review study,” “case study,” “needs further study,” “potential for adoption,” “mixed results.”	Considered “undecided” or "gray zone" unless clarified

Findings

Figure 1 summarizes the bibliometric search parameters and geographic distribution of the 571 case-specific studies. At the regional level, Sub-Saharan Africa contributes the largest share of cases (142, ≈25%), followed by Asia (mainly driven by China and India), Latin America, and North America (primarily the US). Overall, the dataset is concentrated in countries and regions that are among the world’s largest agricultural producers and sites of active agricultural innovation, providing a broadly balanced view of technology adoption across major farming systems, even though it is not a probability sample of all countries.

Figure 1

Overview of the Bibliometric Search Parameter: World Map by Case Frequency

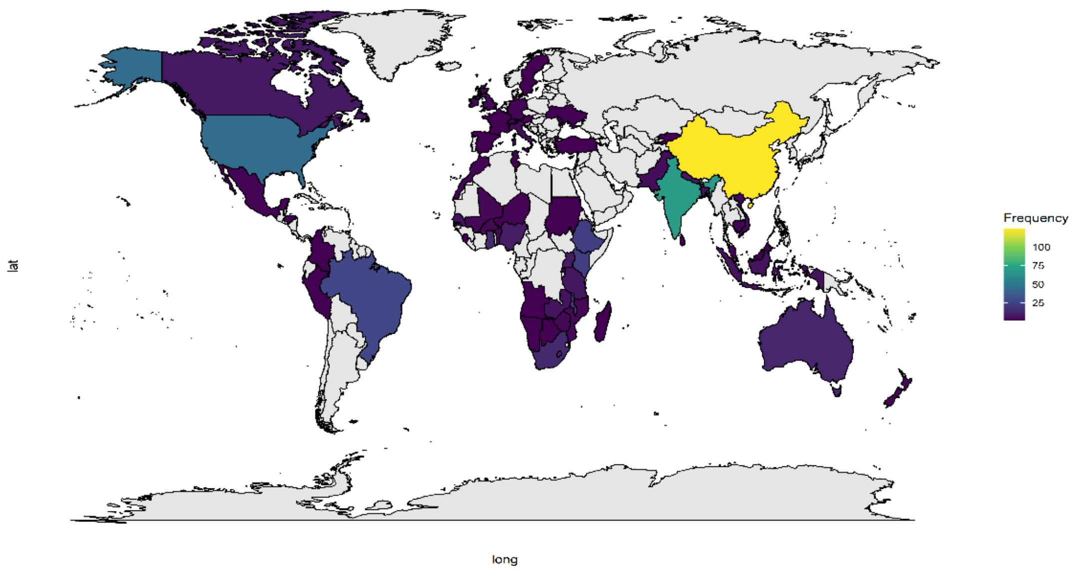


Figure 2 displays a word cloud of innovation types. Conservation appears most frequently (92 cases), followed by management (71), tillage (49), soil (49), process (45), and climate-smart agriculture (CSA) (70 cases in total; 44 instances written as “climate-smart” and 26 as “CSA”). A second tier includes improved (39), digital (35), irrigation (30), integrated (27), precision (26), varieties (26), and sustainable (24). A third tier consists of rotation (19), diversification (19), and intercropping (17).

Figure 2

Overview of the Bibliometric Search Parameter: Word Cloud

Table 2 summarizes the categorical variables and their frequency distributions. The adoption status is roughly balanced, leaning toward No/Partial adoption (54%) over Yes/High (46%). Access to extension and participation in training are slightly less common (51% and 56%, respectively). Rogers-style predictors typically indicate favorable conditions: trialability (57% high) and relative advantage (68% high) are frequently rated as high, and education level (62% high). We used it here as a proxy for literacy and communication skills. Policy support is more limited (64% low/varied). Observability is skewed toward the high category (53%), meaning that farmers can readily see others using the innovation or observe its results in their communities. Climate risk awareness is frequently high (44%), peer networks are mainly medium in strength (50%), and perceived simplicity is predominantly medium (57%), suggesting that most innovations are viewed as moderately straightforward to adopt.

Table 2

Categorical Variable Information

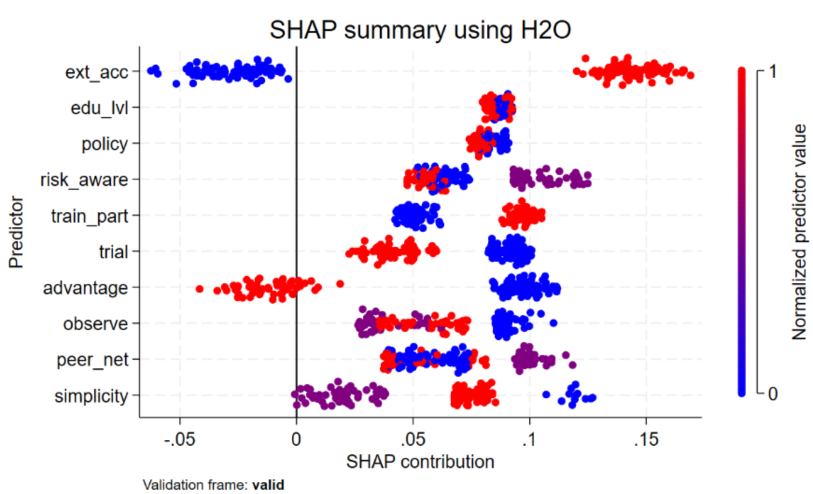
Variable	Variable Name	Category	Cases	%
Adoption status	adopt	No/Partial	307	54
		Yes/High	264	46
Extension access	ext_acc	No	289	51
		Yes	282	49
Training participation	train_part	No	317	56
		Yes	254	44
Trialability	trial	Low/Medium	248	43
		High	323	57
Relative Advantage	advantage	Low/Medium	181	32
		High	390	68
Education Level	edu_lvl	Low/Varied	215	38
		High	356	62
Policy support	policy	Low/Varied	368	64
		High	203	36
Observability	observe	Low	112	20
		Medium	154	27
		High	305	53
Climate risk awareness	risk_aware	Low	168	29
		Medium	155	27
		High	248	44
Peer network	peer_net	Weak	133	23
		Medium	286	50
		Strong	152	27
Simplicity	simplicity	Low	204	36
		Medium	324	57
		High	43	7

Using 5-fold cross-validation, the tuned Random Forest model (*n* = 571) obtained an MCR of 0.244, corresponding to an overall accuracy of about 76%. With a probability threshold of 0.4746 (chosen to maximize the F1 score), the confusion matrix shows that the model correctly classifies 75 of 90 No/Partial adoption cases (error rate 0.167) and 58 of 86 Yes/High adoption cases (error rate 0.326), for 43 misclassifications out of 176 validation observations. The model's AUCPR is 0.732 (compared to a baseline of 0.489), and its ROC AUC is 0.763, indicating good discrimination between higher and lower adoption outcomes and providing sufficiently reliable predictive performance for exploratory decision-support applications.

Figure 3 displays the SHAP (SHapley Additive exPlanations) plot. SHAP values help interpret each predictor's contribution to the RF prediction by showing how high (red) versus low (blue) values shift the probability of adoption. In our model, high values of extension access (ext_acc), relative advantage (advantage), perceived simplicity (simplicity; low complexity), and training participation (train_part) generally increase the predicted probability of adoption, while their low values decrease it. High climate risk awareness (risk_aware), strong peer networks (peer_net), and high observability (observe) also tend to encourage predictions toward adoption. In contrast, low levels of these factors tend to pull predictions toward non-adoption. Collectively, the SHAP patterns suggest that adoption is most likely when farmers have access to extension, participate in training, perceive a clear relative advantage, view the innovation as relatively simple to use, are aware of climate-related risks, and can readily observe peers utilizing the innovation and its results in their communities. Conversely, predicted non-adoption is most common where extension and training are absent, perceived advantage is low, innovations are viewed as complex, climate risks are not salient, and practices are less visible, outlining practical "branches" of conditions that have facilitated or hindered adoption in past studies.

Figure 3

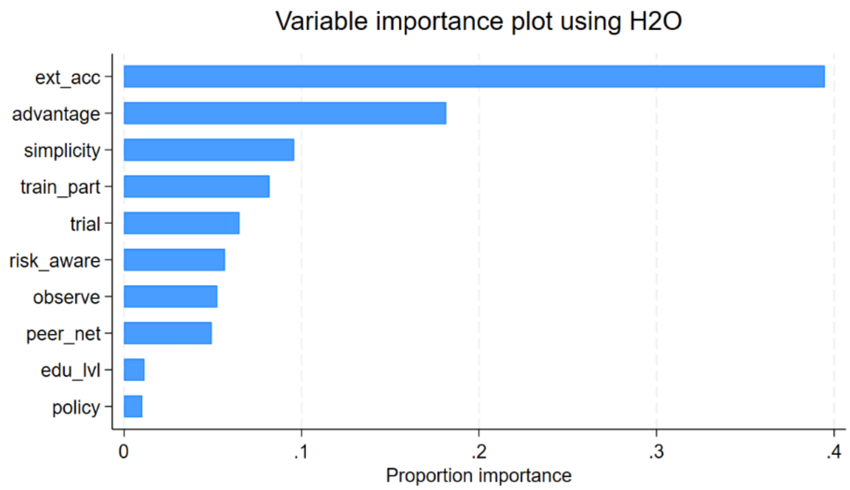
Random Forest Results: SHAP Plot



The variable-importance plot (Figure 4) ranks predictors by their overall contribution to model accuracy. Extension access (ext_acc) is the single most influential predictor, followed by relative advantage, simplicity, and training participation; trialability, climate risk awareness, observability, and peer networks provide moderate additional influence, while education level (edu_lvl) and policy support (policy) play more minor roles in the aggregate model. Importantly, a high SHAP contribution does not necessarily imply high overall importance. For example, education/literacy shows notable local effects in the SHAP plot for specific subgroups but contributes less to global accuracy when permuted. Finally, policy support is only one dimension of the broader external enabling environment; its relatively low importance here indicates that, within this dataset, direct support channels and farmers' own perceptions (e.g., extension, training, perceived advantage, simplicity) are more predictive of adoption than formal policy signals, rather than implying that policy is unimportant in general.

Figure 4

Random Forest Results: Variable/Predictor Importance Plot



Overall, the Random Forest results suggest that agricultural technologies are most likely to be adopted when farmers have direct support (such as extension and training), clearly perceive the benefits, view the innovation as relatively simple, and can observe peers using it. In contrast, adoption is far less likely when these conditions are absent. The close alignment between SHAP patterns and variable importance rankings reinforces the notion that these farmer-level and experiential factors (rather than solely formal policy signals) are the most significant determinants of adoption in this dataset.

Conclusions, Discussion, and Recommendations

Our study combined Boolean searches in two major bibliometric databases with Everett Rogers's diffusion of innovation theory and a Random Forest (RF) machine learning model to synthesize recent evidence on the adoption of agricultural technology. By coding 571 cases and linking them to Rogers-style attributes and contextual factors, we addressed our research questions about which determinants most consistently distinguish higher from lower adoption rates and how AI-aligned tools, such as RF, can enhance diffusion analysis. The RF model demonstrated good predictive performance, and SHAP and variable-importance outputs provided interpretable, theory-consistent insights.

Across innovations and regions, the most influential predictors of adoption were access to extension, perceived relative advantage, perceived simplicity (low complexity), and participation in training, with climate risk awareness, observability, trialability, and peer networks providing additional support. These patterns align closely with Rogers's emphasis on relative advantage, low complexity, trialability, and observability as key drivers of diffusion. Farmers are more likely to adopt when they can access trusted support, clearly see benefits, experience the innovation as simple to use, test it on a limited scale, and observe peers using it successfully. In contrast, adoption is less likely when these conditions are missing, when extension and training are unavailable, the innovation appears complex or risky, or benefits are unclear or invisible. Education/literacy showed strong local effects in specific contexts but weaker global importance, underscoring that its influence is highly context-dependent rather than uniformly decisive.

Although we coded the geographic region of each case and mapped the global distribution of studies, we did not include region as a predictor in the RF model. Region is highly uneven in our dataset (with many cases from a small set of countries) and closely entangled with specific technologies and project designs; including it as a categorical predictor therefore risks masking farmer- and innovation-level mechanisms with broad geographic labels and producing unstable importance estimates. Instead, we used the region descriptively (Figure 1) to illustrate coverage across major agricultural regions and interpreted the "local context" through variables such as access to extension services, climate risk awareness, peer networks, and policy support. Future work with more balanced regional samples and richer spatial covariates (e.g., market access, agro-ecological zones) could model geographic effects more directly.

Our findings also clarify the relationship among Rogers's attributes. Trialability and simplicity are related but distinct: trialability captures whether farmers can experiment with an innovation on a small scale, whereas simplicity reflects the low perceived complexity of the innovation in day-to-day use. Our results suggest that adoption is most likely when innovations are both trialable and perceived as simple, and when they are reasonably compatible with existing practices and resource constraints. Barriers emerged when technologies required significant changes to current systems or were perceived as complex, expensive, or risky, even when other conditions were favorable. Policy support is conceptually important, but in this dataset, it is a relatively weak predictor of adoption decisions. This suggests that direct experiences and support channels for farmers (e.g., extension services, training programs, and peer networks) are more closely linked to the decisions made by farmers than high-level policy signals alone.

Future research should deepen and refine this approach by incorporating additional cases, richer regional and institutional variables, and more granular measures of digital and data-driven innovations. Building on our coding framework, future diffusion studies could also treat innovation-specific features, e.g., cost, risk and uncertainty, training needs, digital and communication infrastructure, market and environmental pressures, resource availability, financial incentives, and farm scale, as explicit dimensions of the "innovation environment," rather than as residual context. Embedding these variables alongside Rogers's five perceived attributes and linking RF-based meta-analysis to household-level datasets, spatial information, and cost–benefit metrics would help clarify under what enabling conditions particular innovations move from early adopters to the early majority, distinguishing technologies that are inherently unattractive from those that are simply poorly supported and identifying levers that policymakers and development programs can use to accelerate or appropriately constrain diffusion.

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