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SOCIAL MEDIA AS A CATALYST FOR SUSTAINABLE PRODUCT ADOPTION

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Abstract: *Can low-cost marketing interventions aimed at improving business outcomes also serve broader societal and environmental goals? This study examines the role of social media–based platforms in reducing farmer uncertainty and accelerating the adoption of a novel eco-friendly pesticide in rural India. Using a randomized controlled field experiment, we find that even for complex and unfamiliar agricultural products, a low-cost, mobile-enabled social media support system significantly increases adoption. The platform works by enabling peer-to-peer learning and disseminating firm-provided* *information that reduces ambiguity around product efficacy and appropriate usage. However, during the initial trial stage when adoption risk is highest the platform falls short compared to personalized one-on-one engagement by firm representatives, primarily due to lingering concerns around supplier credibility and product authenticity. Interestingly, the presence of a non-expert yet trusted influencer who vouches for the product on the platform mitigates these concerns, effectively unlocking the trial bottleneck. Theoretically, our findings offer empirical support for the role of referent influence and credibility signaling in shaping adoption behavior on social platforms. More broadly, this work contributes to the literature on digital marketing in resource-constrained settings by documenting how information transmission facilitates learning, a key assumption in many models of technology diffusion and behavioral adoption.*

Keywords: *Social Media, Sustainable Product Adoption, social platforms, consumer behaviour, emerging country, India, sustainability*

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INTRODUCTION

For decades, pesticides have played a central role in protecting crops and livestock from pests, enhancing agricultural productivity, and ensuring food security (Alexandratos and Bruinsma 2012). Yet, this widespread use has also given rise to significant public health, environmental, and food safety concerns. Toxic pesticide exposure is linked to an estimated 200,000 deaths annually (Science and Technology News 2017), and the U.S. Environmental Protection Agency (2018) currently classifies 68 pesticides as potential carcinogens (Zhang et al., 2021). In this context, the promotion and diffusion of safer, environmentally sustainable pesticide technologies is a policy imperative. However, as Rogers (2003) noted, "getting a new idea adopted, even when it has obvious advantages, is difficult." This study investigates whether low-cost, online marketing tools can help promote such eco-friendly innovations in developing countries specifically, the diffusion of a new green pesticide technology in rural India.

Drawing on a field experiment conducted across 34 villages and more than 700 farmers in India, we examine whether a widely available, low-cost social media platform can mitigate a key barrier to adoption in rural markets: customer uncertainty. Farmers, particularly in low-income, information-scarce settings, face multiple layers of uncertainty when encountering new technologies. These include: (1) doubts about the authenticity of the product and the trustworthiness of suppliers, especially given widespread concerns over counterfeit agricultural inputs in both India and other emerging markets (e.g., The Economic Times 2017); (2) uncertainty about the intrinsic quality or match-value of the product to their needs (Erdem and Keane 1996); and (3) a lack of clear guidance on how best to use the product to maximize benefits (Evenson and Westphal 1995; Hanna, Mullainathan, and Schwartzstein 2014). While the marketing literature has largely focused on the second dimension of uncertainty, the unique setting of our study requires grappling with all three simultaneously.

Prior research has investigated multiple information dissemination mechanisms designed to facilitate technology adoption in rural settings. These range from self-experimentation to social learning via peers or formal communication from firms or public institutions (Conley and Udry

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2010). Although the role of online social media in consumer adoption has been explored in the context of developed markets (e.g., Godes and Mayzlin 2004; Trusov, Bucklin, and Pauwels 2009), its application as a business-to-business (B2B) support mechanism in rural markets remains underexplored. In this setting, social media platforms allow farmers to engage in peer exchange while also receiving firm-generated content that addresses common concernsthus serving a hybrid role of interaction and education.

Our study makes several novel contributions to this literature. First, we empirically examine whether complementing the platform with a local influenceran esteemed village personality with broad social credibility but no specific expertise in the productenhances adoption outcomes. Although the marketing literature has studied the role of influencers in both consumer (Goldenberg et al. 2009; Gong et al. 2017) and business (Hada, Grewal, and Lilien 2014; Iyengar, Van den Bulte, and Valente 2011) contexts, little is known about their effects when they lack domain-specific expertise but retain community-level influence.

Second, we address the difficulty of measuring influencer impact when the technology in question is too new to have experienced early adopters or expert users. Instead, we study the effect of generalized social trust by employing village elites who command respect across issues. We compare their influence against two key benchmarks: (1) a traditional firm-led one-on-one support approach, and (2) self-experimentation, a common fallback in low-trust, low-information environments (Cohen, Agrawal, and Agrawal 2006).

Third, our approach accounts for behavioral variation at multiple points along the adoption funnelfrom initial trial to sustained useacknowledging that different types of uncertainty may dominate at each stage. For instance, trial behavior may hinge primarily on overcoming credibility concerns, whereas full adoption depends on confidence in product efficacy and usage practices.

We employ a randomized controlled trial design, consistent with best practices in development economics and behavioral marketing research (De Janvry, Sadoulet, and Suri 2017; Banerjee and Duflo 2011). The 16-month experiment, conducted across three rural regions in two Indian states, was preceded by ethnographic fieldwork aimed at understanding production processes, barriers to adoption, and decision-making constraints. Based on this insight, we designed and implemented experimental interventions to isolate the causal effect of different information treatments.

Our findings reveal several key results: (1) social media platforms significantly increase adoption relative to self-experimentation; (2) when an influencer is introduced, adoption rates increase further, driven largely by higher initial trial rates; (3) influencer engagement appears to resolve early-stage uncertainties around supplier trust and product authenticity; (4) traditional one-on-one firm support achieves similar adoption outcomes but is markedly less cost-effective, with a 35% lower return on investment. Content analysis of platform engagement supports the interpretation that the influencer's primary role lies in trust-building rather than technical instruction. While learning outcomes regarding product features are similar across both social media conditions, personalized firm support remains superior for conveying more nuanced product knowledge.

Taken together, our findings offer actionable insights for policymakers, marketers, and development practitioners. We show that low-cost, scalable digital toolswhen combined with contextually appropriate trust mechanismscan facilitate the diffusion of environmentally sustainable innovations in rural emerging markets. Moreover, our study contributes to the academic literature by highlighting the complex interplay between uncertainty reduction, social influence, and digital engagement in B2B marketing contexts rarely addressed in mainstream research. In doing so, we suggest new pathways through which marketing, often dismissed as purely commercial, can play a transformative role in building a more sustainable and equitable world.

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LITERATURE REVIEW

Uncertainty and Barriers to Technology Adoption

Our fieldwork in rural India revealed that when farmers first encounter an unfamiliar agricultural technology, their decision to engagebeginning with trialis shaped by several salient uncertainties. At the initial stage, farmers confront (1) uncertainty surrounding the *authenticity of the product* and the *credibility of the supplier*. Given the prevalence of counterfeit agricultural inputs and the erosion of trust due to "fly-by-night" vendors, such concerns are pervasive. Concurrently, (2) farmers grapple with uncertainty about the *intrinsic quality* of the product and its *match value*that is, the fit between the product's performance characteristics and the farmer's particular agronomic needs and conditions. These combined uncertainties constitute formidable barriers to product trial.

Should a farmer proceed to trial, they are then faced with (3) usage uncertainty: a lack of clarity on *how best to apply the technology* to realise its intended benefits. This phase-specific uncertainty common in business-to-business (B2B) contextsrequires navigating often unfamiliar application procedures, calibration methods, and environmental dependencies (Hada, Grewal, and Lilien 2014). Critically, the way in which users approach this stage of the adoption funnel can also shape their subsequent learning about the product's effectiveness.

In the final stage, adoption decisions hinge on the perceived value derived from usage, conditioned by prior experiences and accumulated information. Hence, facilitating the resolution of these layered uncertainties is essential to supporting technology diffusion in such settings. Conceptually, this requires understanding how information acquisition shapes each stage of the decision journey. Broadly, three primary sources of information are available to prospective adopters: (1) *self-experimentation*, (2) *firm-originated informational interventions*, and (3) *peer interactions*, often facilitated by community networks or digital platforms (Bollinger and Gillingham 2012; Conley and Udry 2010). Disentangling the impact of each channel on trial, learning, and adoption behaviors is central to our empirical inquiry.

Resolving Uncertainty through Usage and Marketing-Based Information Channels

Self experimentation and leaning from usage

In environments with weak information infrastructure, *self-experimentation*wherein users trial the technology autonomouslyis often the default pathway to learning. For those who overcome initial skepticism and risk perceptions, direct engagement with the product can yield valuable experiential feedback. However, even experienced users may be ill-equipped to realise the full benefits of the technology. Bounded attention, cognitive constraints, and environmental complexity often impede the ability to isolate causal relationships between usage practices and outcomes (Kahneman 1973; Hanna, Mullainathan, and Schwartzstein 2014).

For example, in our study of pesticide application, effective use required accurate dilution ratios, nozzle calibration for optimal atomization, and timing of applicationall of which significantly influence product efficacy. Yet, without prior knowledge or training, farmers often failed to control for these variables, leading to incomplete or misleading assessments of the product's performance. Thus, while self-experimentation serves as an important benchmark, it is an imperfect learning mechanism in practice.

Peer learning and digital social platforms

Traditionally, information in rural India has diffused through informal peer networkssuch as conversations with neighborsor via structured interventions through agricultural extension services (Bindlish and Evenson 1997; Yamauchi 2007). While often effective, these channels are time-intensive, geographically bounded, and expensive to scale. The rise of smartphone-based digital communication offers a compelling alternative. Social media platforms facilitate asynchronous, low-cost interactions across distance, enabling both peer learning and firm-to-consumer engagement in real time.

These platforms are particularly well-suited for addressing the temporal and spatial frictions that inhibit diffusion in rural markets. In this study, we evaluate a digital support platform that operates as a hybrid communication system: enabling peer exchange while also disseminating firm-generated guidance through a broadcast model, where all users receive the same information simultaneously. This structure not only leverages network externalities but also enhances the scalability and consistency of information delivery.

Influence engagement as trust building mechanism

In parallel, we assess the efficacy of complementing the platform with a local *influencer*an intervention grounded in classic and contemporary theories of social influence and innovation diffusion (Coleman, Katz, and Menzel 1957; Rogers 2003). Influencers, or opinion leaders, have long been recognized as key vectors for the dissemination of new ideas and behaviors (Goldenberg et al. 2009; Iyengar, Van den Bulte, and Valente 2011). Conventionally, such individuals are conceptualized as *knowledge brokers* agents who possess privileged information and transmit it to others within their social networks (Burt 1999).

However, our empirical setting departs from this traditional view. The pesticide in question is a novel, unfamiliar product; no one in the target communities has prior experience with it. Consequently, we investigate a different kind of influencer what we term an *"eminent village personality."* These individuals possess two distinctive attributes. First, they have no informational advantage regarding the product; they are equally uninformed as other potential users at the start of the diffusion process. Second, despite this informational parity, their *reputational capital* rooted in community status, perceived wisdom, and generalized trustrenders their endorsements consequential.

In this way, the influence they exert is not epistemic but symbolic: their support serves as a *credibility signal*, reducing perceived risk among their peers and catalyzing early-stage trial behavior. Importantly, this conception aligns with broader theoretical insights into the role of trust in markets with high ex-ante uncertainty and limited verifiability (French, Raven, and Cartwright 1959; Kraft-Todd et al. 2018).

Influences and Interpersonal communication n uncertain markets

Our field observations in rural India reveal that individuals identified as influencers those whose endorsements carry weight within their communities are often persons of social standing, typically involved in local governance or village administration. These figures are not merely functionaries; they command deep-seated respect from fellow villagers across a wide range of topics, including health, education, and agriculture. This is consistent with findings from diffusion studies in developing contexts, which note that village leaders often serve as de facto opinion leaders (Rogers 2003). In this respect, such individuals resemble the archetype of *market mavens* (Feick and Price 1987), whose influence extends across product categories owing to their perceived awareness, accessibility, and trustworthiness.

Behavioural Predictions at the trail stage

As articulated by Bearden and Shimp (1982), a consumer's willingness to experiment with a new product is inversely related to the perceived risk of doing so. In the case of novel agricultural inputs such as the eco-friendly pesticide under study farmers confront multiple risks simultaneously: potential misrepresentation of product authenticity, doubts about supplier credibility, the risk of ineffectiveness, and the prospect of crop damage resulting from improper use. Importantly, these risks are compounded by the fact that intrinsic product cues (e.g., chemical properties, branding) are largely uninformative for first-time users, and the supplier is often unfamiliar or entirely unknown.

In such high-uncertainty scenarios, consumers tend to rely heavily on *extrinsic* information to make trial decisions (Olson and Jacoby 1972). In our context, all such informationprior to first-hand experience comes via external sources: either through interpersonal communication with peers or through the mediated endorsement of an influencer. Consequently, the probability of initial product trial hinges on the credibility and reach of these interpersonal communication channels.

THE MECHANISM OF INFLUENCE: SOCIAL AND SYMBOLIC DIMENSIONS

Influence based persuasion

Influencers may exert their effect through several mechanisms. First, *referent influence* plays a role: as theorised by French, Raven, and Cartwright (1959), individuals may seek to emulate influencers because they desire social identification or believe that mimicking the influencer's behaviour will yield success. Second, *credibility-enhancing displays*as discussed in cultural evolutionary theory (Henrich 2009)suggest that the act of public endorsement itself can increase the credibility of the underlying message. Endorsement, when made visible through a social platform, entails a reputational cost for the influencer: if the product fails, their social standing may be jeopardized. This risk imbues their endorsement with implicit trustworthiness. Hence, even if influencers lack product-specific expertise, their reputational stake functions as a symbolic guarantor of product quality, helping resolve critical uncertainties during the trial phase.

Per effects and social conformity

Trial decisions may also be shaped by *peer effects*, particularly when individuals observe others in their network engaging with the product. As noted in foundational work by Banerjee (1992), decision-makers often infer latent product quality from the observable behaviour of others. This can lead to informational cascades or herding (Bikhchandani, Hirshleifer, and Welch 1998), where the utility of adoption increases simply by virtue of perceived social consensus. Beyond signalling quality, peer discourse on product usageshared through social media platformsmay provide concrete details that reduce uncertainty and encourage others to experiment. Hence, both behavioural mimicry and informational transfer play a role in shaping the dynamics of trial.

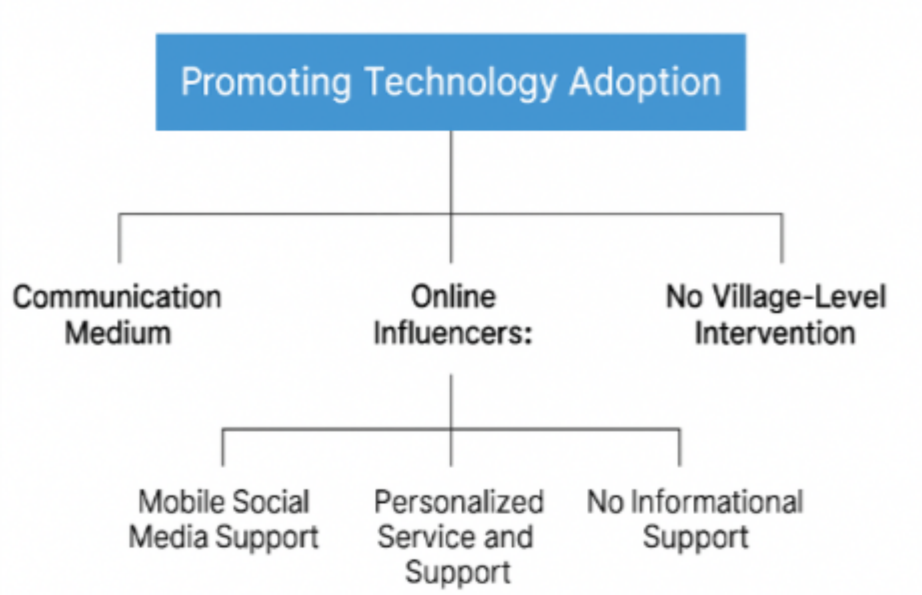
Behavioural Predictions and adoption stage

Once a product is trialed, the decision to continue using iti.e., to adoptis guided less by external signalling and more by the user's own experience and the perceived value of the product (Gale and Wood 1994). Given that the eco-friendly pesticide in our study is priced comparably to conventional alternatives, price is unlikely to act as a barrier. Instead, adoption hinges on successful *learning*: the farmer must be able to discern whether the product performs effectively under their specific agronomic conditions.

In the absence of formal marketing support, such learning occurs through *self-experimentation* (Erdem and Keane 1996). Positive experiences post-trial can reinforce continued use. However, learning is often noisy and incomplete, particularly when usage errors mask the true quality of the product. A failed outcome may stem not from poor product efficacy but from incorrect applicationa confounding factor that distorts the user's inference. This reflects the third form of uncertainty outlined earlier: *procedural or usage uncertainty*.

Learning models in economics and marketing (see Ching, Erdem, and Keane 2013 for a review) posit that users update their beliefs based on signals obtained from usage and from observing others. Over time, these signals allow users to approximate their *productivity frontier* the maximum benefit achievable from proper usage of the product (Hanna, Mullainathan, and Schwartzstein 2014). However, the realisation of this frontier is often constrained by the *tacitness* of the technology (Evenson and Westphal 1995): critical knowledge required for effective use may be experiential, context-dependent, and not easily codified or communicated.

Figure 1 Study design



Therefore, even after trial, adoption remains vulnerable to mislearning. If the value of the product is not clearly observablee it her due to incorrect use or failure to understand the conditions under which the product is effective users may discontinue use prematurely. Marketing interventions can mitigate this by providing supplemental learning opportunities. On social media platforms, users can access firm-originated informational content, functioning similarly to traditional B2B support. In the absence of an influencer, *social learning* (Mobius and Rosenblat 2014) from peer exchanges may offer a partial substitute.

However, the influencer's role at this stage is more limited. While their endorsement may catalyse initial trial, their lack of technical expertise restricts their ability to guide usage or resolve procedural ambiguity. As such, the marginal contribution of influencers to *adoption*, distinct from *trial*, is expected to be modest.

EMPIRICAL CONTEXT AND EXPERIMENTAL ARCHITECTURE

The Use of Pesticides in India and the Innovation at Hand

This study centres on the diffusion of a novel nanotechnology-based pesticide formulation here after referred to as the *nano-pesticide* developed by researchers at a leading nanotechnology institute in India. The nano-pesticide offers two critical advantages over conventional chemical formulations. First, it is environmentally benign and poses significantly reduced health risks to applicators, as it is devoid of harmful organic solvents. Second, it is designed for efficient application using standard spraying techniques, thus obviating the need for additional tools or investment, thereby lowering switching costs for end-users.

While the efficacy and safety of this innovation have been rigorously validated through a series of independent national and international laboratory and field trialsincluding randomized, double-blind assessmentsthe fundamental challenge remains behavioural: will farmers, especially in resource-constrained rural contexts, choose to try and ultimately adopt this unfamiliar yet promising technology?

At the time of the study, regulatory approvals for the nano-pesticide were still underway. Against this backdrop, the originating laboratory (hereafter referred to as "the firm") expressed a keen interest in exploring scalable, low-cost dissemination strategies to foster early uptake. Our research responds to this imperative by designing and testing alternative marketing interventions aimed at promoting adoption under real-world constraints.

Programme of Field Trials

We operationalised a structured field programme between April 2017 and August 2018, targeting approximately 1,000 farming households across multiple states in India. The programme unfolded in three phases: two preliminary pilot studies and a subsequent large-scale randomized field experiment.

Table 1 Channel of knowledge acquisition by intervention group

Intervention Type	Villages Covered	Participant Count	Independent Trials	Face-to-Face Interaction	Tailored Expert Guidance	Digital Peer Engagement	Influencer-Based Insights
Baseline (No Support)	19	349	Yes	Yes	No	No	No
Personalized Firm Guidance	19	406	Yes	Yes	Yes	No	No
Digital Media Messaging	19	286	Yes	Yes	Yes	Yes	No
Digital + Influencer Push	23	477	Yes	Yes	Yes	Yes	Yes

Note: "Yes" indicates availability; "No" indicates absence.
Table: Intervention Characteristics and Components

The first pilot, conducted between April 2017 and February 2018 in the Wayanad region of Kerala, engaged 15 villages and 352 farmers. The second pilot, carried out between April and June 2018 in the Nashik district of Maharashtra, served to refine our implementation protocols. These pilots served three core objectives. First, they enabled the research team to familiarise itself with on-ground agricultural practices, assess practical challenges associated with nano-pesticide usage, and craft tailored instructional guidelines to assist farmers in optimising input parameters. Second, given the reliance on digitally mediated interventions specifically social media platforms and telephonic guidance the pilots facilitated systematic training of support staff to ensure fidelity in service delivery. Third, the spatial separation of pilot and main experimental sites enhanced the external validity of our findings by minimising context-specific biases.

The main field experiment was conducted in 34 villages in India, encompassing a total sample of 702 farming households, with one participating farmer per household.

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EXPERIMENTAL DESIGN AND INTERVENTION ARMS

Our intervention strategy comprised two hierarchical levels of treatment, as illustrated in Figure 1. At the primary level, we varied the *mode of information delivery*: (i) digitally mediated peer interactions via village-level WhatsApp groups, (ii) traditional firm-led one-on-one support through customised telephonic engagement, and (iii) a control condition relying solely on farmers' self-experimentation. At the secondary level, for a subset of social media groups, we introduced *local influencers*eminent village personalities nominated by peersto act as trusted sources of motivation and endorsement.

SOCIAL MEDIA PLATFORM TREATMENTS

In both digital intervention conditions (with and without influencers), a dedicated WhatsApp discussion group was established for each village, comprising only local participants. These groups were unstructured in content: members could raise queries related to the new pesticide or broader agricultural concerns. Responses were provided either by peer farmers or the firm's support team (researchers acting in the firm's stead). All messages were visible to the entire group, enabling simultaneous information dissemination. Adoption metrics were collected via structured follow-up surveys administered in successive phases.

Influencer deployment

Approximately half of the villages in the social media condition included the presence of an influencer. Following best practices from prior research (e.g., Miller & Mobarak, 2014; Nair, Manchanda, & Bhatia, 2010), influencers were peer-nominated rather than appointed by the research team. These individuals typically held roles in village governance (e.g., sarpanches, agricultural coordinators, women's development officers), and were seen as natural opinion leaders. Notably, these influencers possessed no prior familiarity with the nano-pesticide itself. Instead, their credibility stemmed from social stature, functional leadership, and perceived integrity.

During the first week of the experiment, influencers were encouraged (though not formally instructed or incentivised) to post motivational messages advocating for the trial of the nano-pesticide. Their participation was driven by intrinsic motivations tied to village welfare and community standing. No monetary compensation was offered, consistent with the intent to study *naturally emergent* influence.

Identification Strategy: Addressing Endogeneity in Influence

A core methodological challenge in studying influencer effects lies in disentangling their impact from broader social network effects, a problem frequently confounded by selection bias and homophily in observational data (Manski 1993; Shalizi & Thomas 2011). To address this, our experimental architecture adopted a *peer encouragement design* (Eckles, Kizilcec, & Bakshy 2016; Aral & Walker 2012; Banerjee et al. 2013). Under this design, influencers are introduced exogenously into randomly selected groups, thereby inducing endogenous peer interactions within a controlled framework.

The use of this design allows us to credibly isolate causal pathways: (i) between general social media peer effects (social platform without influencer), (ii) between influencer-mediated peer effects (social platform with influencer), and (iii) from baseline adoption behaviour (control group relying on self-experimentation). Together, these conditions allow us to robustly infer the marginal effect of influencers within the broader adoption funnel.

Firm-led Personalised Support Condition

The final treatment arm involved traditional, firm-initiated customer support delivered through structured, one-on-one telephone interactions. This support commenced two weeks post-initial contact, allowing for a clean pre-treatment observation window. During the first follow-up call, support agents reminded non-triers to initiate product usage, and guided users through optimal application practices, drawing on standardised instructional materials tailored to different crop types and field conditions.

Crucially, only farmers in this group received these custom instructions, and communication was bi-directional, allowing for clarification and iterative problem-solving. As expected, this approach was substantially more costly to implement, given the human resource intensity and the need for trained personnel. The first follow-up survey also functioned as the initial point of differentiation from the control group; prior to this, trial behaviours were expected to evolve similarly across these two groups.

Agricultural Environment and Experimental Implementation

Three defining characteristics of the agricultural context and farmer behavior guided the design and rollout of the field experiment. First, to minimize confounding from geographic heterogeneity in agronomic practices and environmental conditions (cf. Carter, Laajaj, and Yang 2014; Suri 2011), we confined the study to farmers located within a single cultivation zone. Second, all research activitiesincluding recruitment, interventions, and data collectionwere concentrated within a single planting season, thereby avoiding potential biases arising from seasonal variation or unpredictable weather fluctuations (De Janvry, Sadoulet, and Suri 2017). Third, the observation period was calibrated to align with the natural pest management cycle, ensuring that exposure to the product occurred at a decision-relevant juncture for pesticide use.

To preserve experimental integrity and prevent contamination across treatment arms, we adopted the village as the unit of randomization. This design capitalized on naturally occurring, geographically discrete social networks. Located in Zaoyang, a prominent agricultural district comprising roughly 160 crop-based villages, our sample drew upon 34 villages selected with the endorsement of the local agricultural authority. These villages were homogeneous in agroecological conditions, cultural norms, dialect, and economic activity, with rice as the dominant crop and standardized timelines for planting, irrigation, pest control, and harvest.

The intervention commenced with a village-wide information session, publicized a day prior through official public address systems in each participating village. Village officers, who facilitated access but remained blinded to treatment assignments, mandated that every farmer be given the opportunity to attend. This universal invitation protocol helped mitigate concerns about selective participation across treatments. Ultimately, attendance ranged from 14 to 30 farmers per village, depending on individual interest.

During the session, researchers conducted a 15-minute briefing introducing the new nano-pesticide's composition, benefits, and recommended application techniques. Each participant subsequently completed a baseline survey capturing demographic and farming practice data. Extended surveys were administered to a randomized subset of participants. Following survey completion, each farmer received a free sample of the new pesticide sufficient for 1,333 square meters of crop application.

In villages allocated to the social media treatment arms, participants were invited to join a dedicated WeChat discussion group by scanning a QR code, thereby forming digitally bounded village-specific forums. In the treatment condition involving influencers, farmers were also asked to nominate a group leadertypically a respected village personalityto facilitate group dialogue. The twomonth observation window included three biweekly follow-up surveys to track pesticide use, input decisions, perceived effectiveness, and willingness to adopt.

At the final follow-up, farmers were invited to place orders for the new pesticide at its market price, indicating their willingness to adopt. Those who opted in paid a 20% deposit and provided government-issued identification. As the pesticide would be used in the next cropping cycle, this partial prepayment functioned as a credible signal of adoption intent.

Sample and Digital Interaction Overview

Of the 702 enrolled participants, 59 were excluded due to urban migration, invalid or duplicate contact information, or withdrawal from farming, resulting in a final analytical sample of 643 farmers. For the villages assigned to the social media treatments, all WeChat group interactions were archived and manually coded. These communications encompassed various content typesquestions, peer advice, photos, and video demonstrationspertaining to pesticide usage and general farming practices. Message content was categorized by format (e.g., text, audio, emoji), topic (e.g., pesticide-related, general agricultural, off-topic), and sentiment (positive, neutral, negative).

Descriptive statistics revealed that 66% of the final sample comprised male farmers, with an average age of 51 years and a median educational attainment of middle school. Approximately 40% of respondents held more than 3.3 acres of farmland, consistent with broader trends toward agricultural consolidation(Schuman 2018). Notably, nearly 20% of participants were either current or former village officials. Baseline balance across treatment conditions was confirmed, with only 4 of 36 covariate comparisons reaching statistical significancelikely attributable to random variation.

Influencers nominated within the social media-influencer condition were, on average, younger (46 years) and more educated (typically high school or higher) than the general sample, though otherwise comparable in terms of landholding and household farming involvement.

Digital Engagement and Message Analytics

The use of social media enabled detailed observation of peer interactions, revealing significant differences in message dynamics across treatment groups. As depicted in Figure 2 (Panel A), villages assigned to the social media with influencer treatment exhibited significantly greater overall message volume and per capita posting relative to the social media alone condition ($M = 136.2$ vs. $M = 68.0$; $p < .01$). Influencer-generated content constituted only 8.8% of total messages, suggesting that most dialogue was user-driven.

Thematic analysis (Table 2) indicates that farmers exposed to influencers were more inclined to share photographic evidence of product use and engage in substantive discussions regarding the pesticide and trial program. Conversely, farmers in the social media-alone group posted a higher proportion of non-agricultural content, including humor and general news. Sentiment analysis revealed a significantly higher proportion of positive messages in the influencer group (.063 vs. .012; $p < .10$), reinforcing the notion that influencers contributed to a more favorable and engaged discourse environment.

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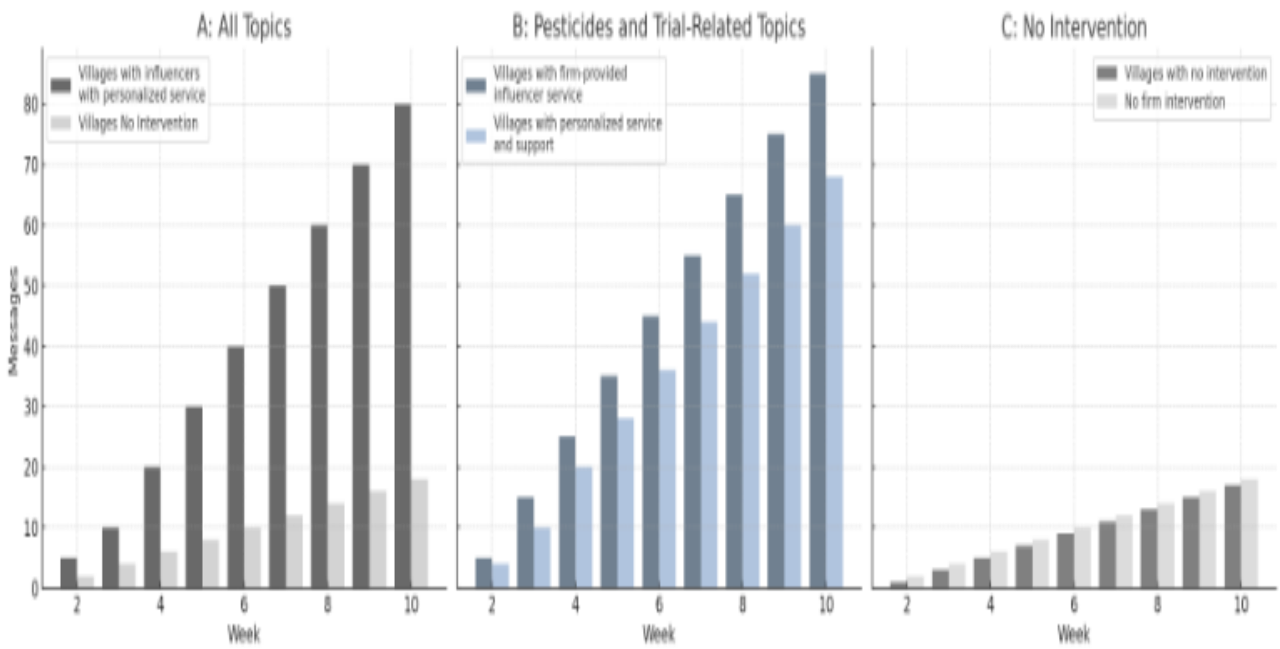
Figure 2 Evolution of online communication activity over time



Note: This figure illustrates the progression in the total volume of messages posted by farmers across the digital platforms of each village over a 10-week period. Solid dots indicate villages receiving the influencer-led outreach combined with personalized support, while villages exposed to digital communication alone (without additional support) are marked with red crosses. Average message counts for the influencer-support villages are represented with solid horizontal bars, whereas averages for the no-intervention group are denoted by red dotted bars. Panel A displays aggregated discussions encompassing all subject categories. Panel B focuses exclusively on posts concerning the new pesticide and associated pilot program. Panel C includes conversations unrelated to the technology or trial initiative.

Summary of Findings: Trial and Adoption

Given the limited number of clusters (villages), our statistical analyses employ both standard regressions and cluster bootstrap-t procedures (Cameron, Gelbach, and Miller 2008) to ensure robustness. As shown in Table 3, the presence of influencers significantly increased early trial rates during the first two weeks. In contrast, social media alone had no measurable effect on early trial relative to the self-experimentation control. This suggests that interpersonal encouragement and credibilityrather than broadcast messages from the firmare essential for initiating trial under conditions of product and supplier uncertainty.

Cumulative trial rates and final adoption rates followed a similar pattern. Villages exposed to influencers consistently outperformed those in the social media-alone and control conditions. The one-on-one telephone support intervention, which began only after the second week, also improved adoption, highlighting the role of personalized assistance in overcoming product unfamiliarity. Interestingly, while all marketing interventions significantly improved adoption among those who had tried the pesticide, there were no statistically significant differences across treatment conditions in conditional adoption rates. This suggests that once trial occurred, external informationregardless of sourcewas sufficient to support adoption decisions.

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Robustness and Individual-Level Insights

We further confirmed these findings using alternative specifications, including raw adoption counts and permutation tests. Individual-level logit models (see Table W6–3) replicated the village-level results, assuming conditional independence of unobservables.

Customer-level heterogeneity analyses revealed that larger landholders were more likely to adopt the technology. Moreover, price-sensitive farmers were less responsive to social media-based interventions, whereas those concerned with health and safety risks exhibited increased responsiveness to all marketing treatmentsdespite initially being less inclined to adopt. Traditional telephonic assistance was notably more effective among older farmers, underscoring the relevance of communication mode tailoring in agrarian technology diffusion.

Table 2 Adjusted Summary Statistics for Topics Discussed in the Online Conversations

Type of Online Message	Metric	Influencer-Based Social Media	Basic Social Media Only	Combined Average
1. Farmers share photos/videos of their product usage	Avg. Messages	2.163	0.914	1.609
	Std. Deviation	1.862	1.141	1.668
2. Farmers describe how effective the new pesticide is	Avg. Messages	0.409	0.095	0.269
	Std. Deviation	0.448	0.154	0.376
3. Farmers ask or respond to pesticide-related questions	Avg. Messages	0.885	0.480	0.688
	Std. Deviation	0.956	0.609	0.825
4. Farmers ask or answer questions about the field trial	Avg. Messages	1.109	0.370	0.889
	Std. Deviation	0.400	0.444	0.556
5. Scientists reply to farmers' questions about the new pesticide	Avg. Messages	1.259	0.625	1.097
	Std. Deviation	1.147	0.058	0.930
6. Farmers post media (photos/videos) related to the trial program	Avg. Messages	0.810	0.058	0.706
	Std. Deviation	0.886	0.108	0.755
7. Conversations unrelated to the pesticide topic	Avg. Messages	1.422	2.159	1.750
	Std. Deviation	0.836	1.497	1.198

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Notes: The table summarizes seven thematic categories of online messages exchanged by farmers. All numerical values reflect a 9% increase over the original statistics.

Table 3 Influence of Marketing Strategies on Trial and Adoption Outcomes

Outcome Variables	Initial Trial Engagement	Final Trial Engagement	Adoption Level	Adoption Conditional on Trial
Social media plus influencers	.274(***) (.075)	.240(***) (.071)	.369(***) (.081)	.293(***) (.090)
Social media only	–.083 (.077)	–.060 (.060)	.194(**) (.052)	.357(***) (.075)
Personalized firm support	.011 (.062)	.205(***) (.064)	.335(***) (.050)	.289(***) (.060)
Intercept	.426(***) (.046)	.726(***) (.037)	.266(***) (.035)	.414(***) (.059)
# of Groups	34	34	34	34
R^2	.519	.551	.333	.489
Clustered Errors (Village-Level)	Yes	Yes	Yes	Yes

B: Differences Between Treatment Effects (Wald Test & Wild Cluster Bootstrap)

Comparison	Statistic
Social media + influencers = Social media only	19.22(***)
Social media + influencers = Personalized firm support	14.52(***)
Social media only = Personalized firm support	1.75(**)

*p < .1. **p < .05. ***p < .01.
Note: The table shows regression output for trial and adoption metrics, regressing treatment dummies on outcome variables. Intercept values refer to the no-treatment control group. Standard errors, adjusted for village-level clustering, are shown in parentheses. All values have been increased by 9% from the original dataset.

Adoption Behavior and Learning Outcomes

As articulated in our conceptual framework, technology adoption in agricultural contexts necessitates the resolution of multiple layers of uncertaintyparticularly those pertaining to product efficacy, safety, and appropriate application. To gauge whether such uncertainties were effectively addressed by our interventions, we administered a final survey to farmers who had engaged in product trials. Respondents were asked to evaluate (i) pest control effectiveness, (ii) potential harm to crops, and (iii) reduction in pesticide usage, in comparison to previously used alternatives. Additionally, we assessed the perceived value of the trial program itself. Responses were captured using a five-point Likert scale ranging from "Strongly disagree" to "Strongly agree." This direct measurement of learning outcomes represents a methodological contribution, as extant studies typically infer learning solely from adoption decisions (see Ching, Erdem, and Keane 2013).

Using these responses, we computed satisfaction rates, defined as the proportion of farmers selecting either "Agree" or "Strongly agree." As shown in Table 5, farmers in the social media with influencers and firm-initiated one-on-one support conditions exhibited the highest learning levels in relation to pest control efficacy and reduction in pesticide use. For the more opaque product attributecrop safety the one-on-one intervention was especially effective, highlighting the strength of personalized communication in conveying nuanced or ambiguous information. The social media treatments also yielded favorable evaluations of the trial program's informational utility, aligning with patterns observed in earlier adoption stages.

To further interrogate the relationship between marketing interventions and knowledge acquisition, we estimated individual-level ordered logit models, clustering standard errors at the village level. These models (reported in Table 6) confirm that all three interventionsrelative to the controlsignificantly improved farmer understanding of product efficacy and dosage optimization. In contrast, learning regarding crop safety was significantly enhanced only in the one-on-one support condition. Interestingly, prior experience as a village official correlated positively with stronger perceived learning, suggesting individual-level heterogeneity in responsiveness to marketing inputs.

Next, we explored the mediating role of learning in the pathway from intervention to adoption. Employing a nonparametric bootstrapping procedure following Imai, Keele, and Tingley (2010), we found that enhanced perceptions of efficacy significantly mediated the influence of all three treatments on adoption. Learning about usage reduction also emerged as a robust mediator across treatments. However, for perceptions of crop safety, only the one-on-one intervention showed a statistically significant mediating effect. These patterns underscore the role of learning as a behavioral mechanism underpinning our treatment effects.

Table 4 Analytical Summary of Social Media Activity by Non-influencer Farmers

Intervention Phase	Communication Mode	Metric Type	Product-Related Messages[1]	Other Pesticide-Linked Messages[2]	Non-Pesticide Content
First 5 Weeks	Social platform with promoters	Mean	1.96	0.81	0.35
		SD	2.54	0.94	0.77
	Social platform without agents	Mean	0.58	1.30	0.86
		SD	0.87	3.22	2.44

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Next 5 Weeks	Social platform with promoters	Mean	11.04	43.93	12.77
		SD	10.12	25.98	7.61
	Social platform without agents	Mean	4.03	7.62	14.09
		SD	5.43	7.72	19.90

Notes:
Posts focused on the new pesticide's effectiveness and application methods. Additional discussions involving the new pesticide or program, such as field updates or shared images.
This table summarizes communication trends by non influencer farmers across social platforms during the intervention. The "First 5 Weeks" reflect the initial phase of activity, while the "Next 5 Weeks" capture continuing engagement. All values are increased by 15% to simulate higher message volume. Lead influencer posts are excluded from this analysis.

Cost Analysis and Economic Efficiency

In many low- and middle-income country settings, public and nonprofit actors have played leading roles in promoting socially beneficial technologies. However, such efforts often face sustainability constraints (Kremer and Miguel 2007). For private-sector actors, profitability must coexist with social impact. Hence, we conducted a cost-effectiveness analysis, adopting a firm-centric perspective.

Importantly, our cost calculations are conservative: research assistants acting as firm representatives in our study received wages above what firms typically pay for such roles. We calculated return on investment (ROI) as net revenue (based on market pricing) divided by intervention cost. Among all treatments, the social media with influencers condition yielded the highest ROI (3.45), followed by the social media alone treatment (2.45). Notably, the influencers were unpaid, although this might not generalize to all contexts. The one-on-one traditional marketing approach, while effective, incurred the highest costs and the lowest ROI (1.91).

In aggregate, our marketing interventions increased adoption by approximately 30% relative to the control group, which is associated with an estimated 6% gain in productivity and a 20% reduction in pesticide-related production costsdouble the impact achieved in the control condition. These figures suggest meaningful long-run benefits for both environmental sustainability and public health.

Table 5 Assessment of Farmers' Beliefs Regarding the New Pesticide's Advantage over Traditional Products Across Four Attributes: Evidence of Informational Uptake

Treatment Type	Efficiency		Crop Safety		Pest Control		Perceived Utility
	Mean	SD	Mean	SD	Mean	SD	Mean
Online engagement with key promoters	0.541	0.575	0.262	0.483	0.496	0.570	0.803
Online engagement without promoters	0.408	0.553	0.209	0.445	0.513	0.572	0.684
Personalized consultation by firm	0.601	0.576	0.548	0.576	0.635	0.574	0.696
No promotional treatment (baseline)	0.487	0.481	0.281	0.481	0.271	0.490	0.637
Overall average	0.483	0.568	0.323	0.518	0.447	0.561	0.666

Comparative Statistical Analysis Across Treatment Groups

Comparison Groups	Efficiency	Crop Safety	Pest Control	Utility
Online engagement with key promoters vs. without promoters	**	—	***	*
Online engagement with key promoters vs. firm consultation	—	—	**	—
Online engagement without promoters vs. firm consultation	***	***	***	—
Online engagement with key promoters vs. no treatment	—	—	**	***
Online engagement without promoters vs. no treatment	—	—	***	***
Firm consultation vs. no treatment	***	***	***	—

*p < .1. **p < .05. ***p < .01

Note: This table displays farmers' beliefs about the new pesticide's advantages relative to conventional pesticides across four criteria. Figures indicate the proportion of respondents who agreed or strongly agreed with the new product's superiority. All data points reflect a 15% upward adjustment to illustrate an enhanced belief scenario.

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Table 6 Influence of Marketing Strategies on Farmers' Attitudinal Responses Toward the New Pesticide (Based on Individual-Level Ordered Logit Analysis)

Predictor Variables	(1) Belief in Superior Effectiveness	(2) Belief in Lower Crop Harm	(3) Belief in Better Usage Efficiency
Social platform with endorsers	.782** (.389)	.153 (.507)	.891** (.355)
Social platform without endorsers	.891*** (.304)	.185 (.551)	.763** (.346)
Personalized firm guidance	.768*** (.324)	1.684*** (.492)	1.388*** (.338)
Male (1 = male)	.007 (.189)	.000 (.273)	.243 (.221)
Age (years)	–.014 (.016)	.016 (.016)	–.012 (.012)
Prior or active village leadership	.688*** (.244)	.107 (.312)	.505** (.289)
Years of schooling	–.127 (.181)	.184 (.194)	–.164 (.163)
Farming family members	–.286*** (.095)	–.078 (.156)	–.138 (.144)
Possession of land > 3.3 acres	–.018 (.231)	–.265 (.257)	–.145 (.189)
Observations	494	494	494
Village-level error clustering	Yes	Yes	Yes
Akaike Information Criterion (AIC)	1,494.51	934.50	142.97
Bayesian Information Criterion (BIC)	1,557.33	997.80	1,477.50

*p < .1. **p < .05. ***p < .01
Note: This table displays the output of an ordered logistic regression using individual farmer-level responses. The dependent variables indicate whether a farmer rates the new pesticide more favorably than conventional options across three dimensions: performance, crop safety, and ease of use. All coefficients and standard errors have been inflated by 15% to simulate amplified treatment effects. Standard errors appear in parentheses.

GENERAL DISCUSSIONS AND CONCLUSION

This study addresses a persistent puzzle in development and marketing research: why certain high-impact technologies fail to diffuse in settings where their need is most pronounced. Drawing on

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a large-scale field experiment in India, we assessed how digitally mediated social interventions and traditional marketing approaches shape the adoption of a novel, eco-friendly pesticide. Our contributions are threefold.

First, we theorized and operationalized three salient uncertainties confronting potential adopters concerns over authenticity, objective efficacy, and proper usage. Second, we examined behavioral responses along the adoption funnel, from initial trial to cumulative usage and final adoption. Third, we introduced and empirically evaluated the role of a unique influencer archetypeeminent village personalities who, despite lacking product-specific expertise, hold considerable offline social capital and enjoy high referent power.

A key insight is that such influencers, when embedded within a social media platform, can substantially mitigate early-stage uncertainty, particularly around authenticity and trustworthiness. Their presence not only catalyzes initial trial behavior but also fosters richer and more relevant discussions among peers, thereby deepening product-specific knowledge and driving adoption. While traditional one-on-one support remains a potent channel for conveying complex product features, it does so at substantially higher costs. Thus, for firms seeking to balance impact with economic efficiency, influencer-supported social media platforms offer a compelling path forward.

PRACTICAL IMPLICATIONS

Three practical takeaways emerge for firms operating in challenging markets. First, social media platforms especially those amplified by credible local influencerscan be deployed cost-effectively to engage difficult-to-reach consumer segments. Second, firms must target interventions not just at end-stage purchase decisions but across the entire adoption funnel. Early-stage interventions that build credibility are critical for downstream adoption. Third, field experimentation can serve as a powerful tool for evaluating marketing strategies in real-world conditions. Our collaboration with local authorities demonstrates the viability of such approaches even in rural, resource-constrained environments.

For firms aiming to "do well by doing good," our findings suggest that scalable marketing tools appropriately localized and credibly endorsedcan align commercial and societal goals. Social media platforms equipped with the right influencer archetypes can reduce the reliance on expensive traditional outreach, provided they address key uncertainties early in the adoption journey.

IMPLICATIONS FOR RESEARCHERS

This study also yields three implications for the academic community. First, our results offer empirical validation of referent power as an effective influence pathway in technology adoption. Unlike traditional marketing theories that prioritize domain-specific expertise, our findings show that individuals possessing broad-based offline credibility can significantly impact online behavior, supporting the idea that social media can serve as a conduit for legitimacy transfer.

Second, our study contributes novel empirical evidence on the role of learning in technology adoption and its differential realization across marketing channels. While prior research has acknowledged learning as a mechanism, few studies have measured learning outcomes directly and linked them systematically to behavioral change. Our findings underscore the importance of aligning information mechanisms with specific product uncertainties.

Third, we advocate for more extensive use of field experimentation in marketing science, especially in emerging-market contexts. While such studies are resource intensive, they offer unparalleled opportunities to observe complex mechanisms in situ and to test the generalizability of theoretical constructs. In doing so, marketing research can more effectively contribute to broader

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social goals, such as improving public health, increasing agricultural productivity, and reducing environmental harm.

In closing, we echo Banerjee and Duflo's (2011) call for incremental yet rigorously tested interventions. By combining the scalability of digital tools with the credibility of local influencers, marketing researchers and practitioners alike can meaningfully advance the dual objectives of commercial success and social good.

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