Agriculture and Human Values (2023) 40:1205–1220
https://doi.org/10.1007/s10460-023-10415-9

Male and stale? Questioning the role of "opinion leaders" in agricultural programs

Petr Matous[1]

Accepted: 12 January 2023 / Published online: 19 February 2023

Abstract

Social networks can influence people's behaviour and therefore it is assumed that central individuals in social networks, also called "opinion leaders", play a key role in driving change in agricultural and food systems. I analyse the outcomes of an intervention (that encouraged Sulawesi smallholder farmers to take a specific action toward improving the health of their cocoa trees) to assess the impact of engaging opinion leaders in agricultural programs that aim to change farmers' practices. The intervention has been implemented through (a) 18 opinion leaders identified by interviews and a social network survey of 1885 cocoa farmers; and (b) 18 randomly selected farmers who were not central in local social networks. The obtained social networks and statistical data were quantitatively analysed and the results were interpreted with input from the field staff. Contrary to expectations, the highly socially central opinion leaders were not more effective in promoting the initiative in their communities. On average, randomly selected low-centrality farmers convinced almost twice as many of their peers to take the recommended action as compared to the identified opinion leaders (17.1 versus 8.6) but the variation within the random group was also significantly higher. Importantly, while the identified opinion leaders were mostly senior men, women performed better in influencing others into taking action even when their centrality in local social networks of agricultural advice was lower. I discuss the implications of the conventional selection of perceived opinion leaders as model farmers for achieving sustainable and equitable change at scale in agriculture and propose practical alternatives.

Keywords Opinion leaders · Model farmers · Social networks · Smallholder agriculture · Development programs

Introduction

Global agricultural production relies on millions of farmers and especially in lower income countries a large proportion of them are economically and ecologically vulnerable smallholders whose central concern is typically the satisfaction of basic human needs (Terlau et al. 2019; Cafer and Rikoon 2018). These numerous small independent actors are highly heterogeneous, often strongly influenced by local social norms and characterised by high future discount rates. Those who own their land are formally not anyone's employees and therefore have theoretically high degrees of freedom in how they cultivate it (Llewellyn and Brown 2020). However, sustaining long-term functionality of agricultural systems under changing socio-environmental conditions requires both small and large changes on behalf of these farmers, many of whom are based in regions with weaker institutions and inadequate supporting infrastructure (Llewellyn and Brown 2020). While they can be in some cases convinced to take certain actions *en masse* by changing regulation and accreditation conditions, export rules and large buyer's requirements, the farmers' understanding and interest in improved and more sustainable practices cannot be all entirely coerced centrally in a top- down manner. Changing their attitudes and winning their hearts and minds is often required as a part of agricultural system transitions toward sustainability (González and Nigh 2005; Neilson 2008; Barrett et al. 2001; Meemken and Bellemare 2020).

While transformative changes towards sustainability include radical system restructuring, adaptive changes include smaller incremental actions, such as tweaking one's practices (Barnes et al. 2020; Cinner and Barnes 2019) and smallholder farmers can ostensibly be steered into these smaller actions via their social environment (Boun My et al.

✉ Petr Matous
petr.matous@sydney.edu.au

[1] School of Project Management, Faculty of Engineering, University of Sydney, Ross Street 21, Forest Lodge, Sydney, NSW 2037, Australia

2022). International development programs in the agricultural sector that aim to achieve such positive changes across vast regions covered by numerous small farms, are routinely implemented through pilot programs and training initiatives with a limited number of selected individuals, most commonly referred to as "model farmers" (Taylor and Bhasme 2018). These programs implicitly or explicitly rely on social networks to lead to scaling up of impacts from the model farmers to others (Feder and Savastano 2006). Typically, the preference in the selection of model farmers is to be proactive, responsive to incentives and as locally influential as possible to maximize the intervention impact on the community (Alamgir Hossain and Crouch 1992; Alexander et al. 2020).

The practical focus on capturing the most prominent actors in local social networks is rooted in a long tradition of academic research on "diffusion of innovations" (Valente and Davis 1999; Rogers and Cartano 1962; Rogers 2003). Based on a long line of research that evolved from this tradition, we now know that network links can channel useful resources, knowledge and tangible influence between farmers and this has been repeatedly reconfirmed in numerous studies of agriculture and food systems (Skaalsveen et al. 2020; Kabirigi et al. 2022; Slijper et al. 2022; Li et al. 2021; Tian et al. 2021; Munthali et al. 2021; Isaac 2012; Cofré-Bravo et al. 2019; Feder and Savastano 2006; Martini et al. 2017; Rust et al. 2022; Labeyrie et al. 2014, 2016, 2021; Brinkley et al. 2021; Parks 2022; Rockenbauch and Sakdapolrak 2017; Rockenbauch et al. 2019; Wu and Zhang 2013; Trivette 2019). From these findings, it may appear almost self-evident that targeting behaviour-altering interventions at farmers who have more social network links will scale up more widely than interventions involving socially peripheral members of rural communities. However, the mixed outcomes of programs that aim to promote more sustainable and food secure agriculture at scale suggest that the reality is more complex (Woltering et al. 2019; Sartas et al. 2020). Exploring the channels of successful diffusion, studies have delved into the roles of different types of network centralities, such as degree versus betweenness (Zhang et al. 2020) and different types of network links, such as strong versus weak ties (Darr and Pretzsch 2008; Nelson et al. 2014), providing important theoretical insights and practical training manuals to enhance and leverage the right types of networks and better target farmers by extension services (Khanal et al. 2020). It is clear from these previous analyses and open-ended inquiries that there are numerous factors which can potentially influence the diffusion and adoption of recommended agricultural practices and centrality in knowledge-sharing networks is generally considered to be one of them (Wood et al. 2014).

Here I test some traditional assumptions that drive in practice which model farmers are usually selected to participate in agricultural programs and interrogate the idea that relying on network centrality as the dominant selection criteria will lead to desired impacts. Specifically, using data from a practical experiment implemented among Indonesia cocoa farmers, the main research question of this study is: Are model farmers who are central in their local social networks really more effective in immediate scaling up of an adaptive agricultural intervention than others?

Championing change among smallholder farmers

Development program managers, extension practitioners as well as large food manufacturers who rely on sustained productivity of smallholder farmers in their supply chains have been searching for ways to effectively promote change among large numbers of independent producers, who are typically not obliged to follow their recommendations. The practical approach has often been to target change initiatives at model farmers who have a track record of being cooperative in previous programs, who are considered to have the authority to speak on behalf of the community and who are considered to be of influential social standing within the community and thus able to inspire others to follow their example, i.e., to act as opinion leaders (Taylor and Bhasme 2018; Feder and Savastano 2006). The following subsections explore the intellectual roots and some of the challenges of this model.

Lazarsfeld and Katz's two-step model

Although not many agricultural program organizers might be familiar with the original "two-step model" (Katz 1957), Lazarsfeld and Katz's body of work has since the 1940s shaped our thinking on how ideas and social innovations diffuse through society, including through communities of smallholder farmers. The two-step model has given rise to the concept of "opinion leadership" that has been hugely popular across diverse fields of research and practical applications until the present day (Katz 1957). The model describes how information and social influence flow across societies in two steps: (1) a small proportion of population labelled "opinion leaders" pay attention to official information channelled through formal channels and (2) the rest of the population that does not follow or does not have access to the official information channels receives the information second-hand from the opinion leaders (Katz 1957). The model contributed to the theory by recognizing that information and influence do not spread uniformly across atomized populations but through networks of interpersonal relationships. The model posits that people are mostly persuaded by give-and-take with other people and that some people are more important than others in this give-and-take and consequently in the transmission of influence. Such individuals are present at every layer of the society and are recognized by the fact that their peers ask them for advice in their domain of opinion leadership (Katz 1957).

It is now over 70 years since the original studies and the core ideas are still widely applied. However, some nuance might have been lost over the decades. It seems to be assumed in widespread current applications that if a small number of correctly identified opinion leaders are supplied some information or innovation, they will automatically and successfully disseminate it to their followers (Centola 2021). In the social media era, the search for individuals who can influence many others has received further boost. Opinion leaders have been rebranded as "influencers" and the conviction seems now stronger than ever that the way to effectively influence large numbers of people is to find influencers in the domain of interest and work with them (Centola and Macy 2007). The evidence for that is patchy in the context of smallholder agriculture.

Within the first step of the two-step model, studies in the field of "diffusion of innovations" have over decades analysed the attributes of opinion leaders (Rogers 2003). In the second step, networks studies have traced the spread of the phenomena in focus from their original seeds to the rest of the population (Valente 1995; Centola et al. 2007). However, the willingness and ability of opinion leaders to proactively collaborate and influence their identified followers within social networks has often been taken for granted. In the original two-step model, opinion leaders where individuals who obtained information from official mass media. How opinion leaders of today engage with formal information and whether and how this can be leveraged for agricultural systems' sustainability and equitability needs to be questioned. There is no guarantee that opinion leaders in remote agrarian communities are waiting for development agents to come and tell them which ideas to spread to their competitors (Zhang et al. 2020). Even when it is advantageous for them, for reasons summarised in the following subsections, they may still not necessarily be the most suitable individuals to recruit as model farmers for adaptation initiatives that may require the community members to change their habits or adopt practices that are at odds with their routines.

Challenges at step one: influencer fatigue

Although organizations implementing interventions in agrarian communities prefer working with well-accessible and socially visible model farmers with necessary communication skills and a track record of smooth collaboration with external agencies, it is not clear whether these attributes translate to high engagement and willingness to share the information and resources acquired from external agencies to others (Taylor and Bhasme 2018). In the context of competitive markets or ethnic fragmentation, local network brokers may in fact be actively disinclined to channel advantageous information to others (Barnes et al. 2016). Moreover, while repeated engagement by international institutions may elevate leading farmer's visibility within the community, frequent requests to promote external programs that have more public than private benefit may also gradually decrease the high-status farmers' motivation to do so (Taylor and Bhasme 2018). Furthermore, farmers' position in visible local roles, such as in extension support, cooperatives or farmer groups can be both a cause and a consequence of high social network centrality but individuals in these roles do not always demonstrate actual high willingness and capability to positively change the behaviour and practices of others. Specifically in Indonesia, it has been observed that these roles have become ineffectively and inequitably "masculinized", with the trend being further reinforced by informal networks surrounding these roles (Wijers 2019; Ford and Parker 2008; Parker 2008). Also, being an opinion leader in a conservative community does not mean being progressive or welcoming of external influences toward change (Zhang et al. 2020). Even opinion leaders are highly affected by their peers (Katz 1957). Opinion leaders are respected by others because their actions are in line with the community norms and values and they may not want to lose their prestigious social standing by going against local status quo because an external technical expert or project manager asked them to do so (Rogers 2003). Already Katz (1957) observed that interpersonal relations are a source of pressure to conform to a group's way of thinking and by extension, those who have more of such relations may experience more pressure to conform.

Challenges at step two: influencers backfire

Research outside of agricultural contexts has shown that social diffusion is often significantly different from epidemiological diffusion in which highly central individuals in social contact networks can quickly infect a disproportionately high number of people (Centola and Macy 2007). Superficial awareness knowledge of simple issues that may spread simply just by hearing about something once from a single source may be relatively similar to viral spread in which central individuals with many links, or many followers, are effective seeds to trigger such simple types of contagion (Centola 2021). However, a diffusion of behavioural change is more complex than the spread of awareness (Centola 2010). Hearing about something from a single source will not necessarily motivate us to change our habits (Centola 2021). Farmers may be naturally hesitant to change their practices and risk their livelihoods if they hear about a new approach only from the district's social star engaged by an external agency. Some will want to see what closer friends within their closer social niche think about it, whether they have tried it, whether it worked for them, whether anyone in their family tried it too and whether it worked for them too (Matouš et al. 2013). Therefore, as the theory of complex contagion goes, awareness of new practices can outpace their acceptance, if seeded through central individuals with many links. The situation when everyone is aware of a promoted innovation and also aware of the fact that none of their close friends has adopted it yet can lead to a collective perception that this innovation has been locally rejected before it could even be given a chance. Centola (2021) has labelled this phenomenon "influencers backfire" effect. Another potential downside to employing high-status opinion leaders as model farmers is that they may not be quite like the rest of the community. Due to human's general tendency towards homophily (McPherson et al. 2001), it has been empirically observed that with increasing social disparity between opinion leaders and their followers, the leaders' potential for broad impact diminishes (Feder and Savastano 2006). Being too prominent can make one atypical and irrelevant.

Methods

As reviewed in the previous sections, this study tests some common, although often implicit, assumptions that have roots in the two-step model pioneered in Western urban settings in the 1940 and 1950 s. In the following decades, the concepts from this model widely spread to non-Western low-income settings (e.g., Chatman 1987). Finally, with the rise of social media, ideas about opinion leaders have become increasingly shaped by the notion of "influencers" in online settings (e.g., Rust et al. 2022). Here, I analyse the outcomes of a practical offline experiment in a non-WEIRD (non-Western Educated Industrialised Rich) rural context, which is a more relevant setting to where most smallholder farmers are located (Terlau et al. 2019). The experiment specifically tests whether coached central farmers identified by a combination of sociometric surveys and interviews (i.e., opinion leaders who were reported by others as their source of agricultural information and whose willingness to participate was confirmed) can make more peers take a particular farming-related action as compared to random low-centrality farmers.

Intervention design

It is problematic to implicate influence from observational studies of standard programs with all real-world confounding factors or from a retrospective examination of phenomena that has already naturally diffused through a network. Retrospective non-interventionist studies can identify characteristics of individuals that have diffused new trends but it does not mean that these individuals would be the optimal and willing seeds in schemes devised by outsiders. This study is based on an intervention implemented by a non-governmental development organization (Swisscontact) as a part of their operations in Indonesia. Funded mainly by international governments and food productions companies, the organization had been regularly surveying all certified cocoa farmers in Sulawesi to understand the social barriers and leverage points for the improvement of local farming practices. Such comprehensive surveys were possible because all certified cocoa farmers in the district were continuously tracked and their details updated in a database for traceability purposes of the certification. At the end of 2019, the survey included the question: "Please mention people outside of this household, you talked to in the last 12 months to solve problems and get advice or useful information related to farming practices, especially about cocoa". While administering the survey in the field, each elicited advice giver was uniquely identified by their ID in the district cocoa database and their correct identity confirmed with the respondent in real time. Out of 2061 eligible certified cocoa farmers in the district network, 1885 were managed to be surveyed in this survey (91%). This data forms the basis of social network mapping in this study. For illustration purposes, the largest interconnected component of the advice sharing network among 638 farmers is visualized in Fig. 1. (For visibility, the rest of the sample, i.e., other topological components of the network, are not included in this space-constrained visualization.)

For the purpose of this experiment, the partner organization structured one of their field initiatives in a way that

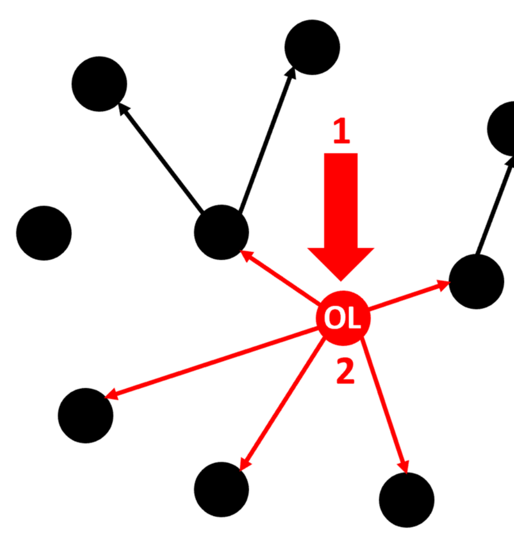

Fig. 1 Lazarsfeld and Katz's two-step model—socially central opinion leaders receive information from official channels and diffuse it across the society through informal network links

allowed to quantify the respective impacts of high-centrality and low-centrality farmers in promoting a recommended action. The project was implemented in one anonymized district of Sulawesi in the beginning of March 2020 (just before the Covid19 pandemic started affecting the operations and interactions of Sulawesi farmers in these remote areas) with the intention to provide evidence-base for network-informed selection of model farmers for further practical interventions in the area. The author has obtained a completely anonymized network data of all certified cocoa farmers in the district and the data on the age, gender, and education of direct participants in the intervention. The farmers have provided written consent that their data may be used for research and the study was approved by the human research ethics committee at the University of Sydney.

Agricultural experiments and pilot projects are often set up and managed in highly controlled environments that complicate transition to real world settings (Woltering et al. 2019). To maximize external validity, the present intervention was designed to resemble in practice as closely as possible other common large-scale programs conducted by this and other development organizations in agrarian communities in which purposefully selected farmers are recruited to adopt and diffuse a certain practice. The intervention was of the common type of agricultural programs, which provide free or subsidized resources that convey private visible benefits to participating farmers and their role is to entice large numbers of other farmers to also adopt it. Substantially, the intervention aimed at increasing awareness and stimulating action towards maintaining cocoa tree health by pruning. For the purpose of measurement, the specific action to diffuse had to be one that is directly observable with a clearly attributable source of influence. The aim was to gather information on influence among farmers immediately while they were taking action stimulated by the intervention, in contrast to information on self-reported retrospective or hypothetical sources of influence. This was a challenging aim for a practical real-world intervention in an offline remote rural setting. It required some simplification with a focus on just a small adaptive change as larger technological changes typically require more complex reconfiguration of social and technical components of agricultural systems (Glover et al. 2019).

In this intervention, the field staff visited all participants, explained the importance of pruning to them and gave them free pruning scissors, which they appreciated. It was explained to the farmers that pruning is an inexpensive way to increase yield of cocoa trees by optimizing their growth patterns (Adomaa et al. 2022). Increasing yields without additional costly inputs was of great interest to the farmers. It was explained that correct pruning of cocoa trees decreases unwanted shading, helps control diseases and pest and limits transfer of nutrients to unproductive parts of the plant (Tosto et al. 2022). The participants were asked to share the importance of pruning with their peers and to recommend to them to also obtain free pruning scissors from the implementing organization by contacting the organization and mentioning the name of the original program participant who told them to do so. The number of farmers each participant influenced to take this recommend action was counted as the intervention outcome.

Participant selection

As in other practical agricultural development programs, the implementing organization aimed to purposefully engage model farmers who could were generally expected to deliver good outcomes for the program due to their opinion leadership status. Additional, to quantify the added value of such deliberate opinion leader engagement, a group farmers who were not considered opinion leaders were also engaged for comparison, which would not be done in other business-as-usual initiatives. The participant selection from the opinion leader pool was not purely randomly the way it would be done in academic randomized controlled trials, but never in practical initiatives when scholars are not involved (Muller 2015). The purposeful selection was informed by interviews and opinion of the local field staff and was motivated by the partner's practical goal to engage with maximum impact the identified opinion leaders in further coaching and delivery of future development programs in the area. The details of the selection are below.

In the first stage of the opinion leader selection, top 10% of the highest centrality cocoa farmers in the district were identified purely quantitively based on a network centrality metric called indegree. Indegree in advice networks equals the number of times a network actor has been named by others as their advice giver. An actors' indegree is based on answers of everyone else in the network and it is not affected by the actor's own responses. High indegree means that a high number of respondents independently nominated the same person as their advice giver. The number of nominations by others is a fundamental and well-established classical network measure of opinion leadership (Rogers and Cartano 1962) that has been further extended and formalized later through the development of network research methods (Valente 1995; Valente and Pumpuang 2007; Valente and Foreman 1998). While indegree is typically correlated with other network centrality metrics, it tends to be more robust to quality issues in data that may affect (without the researchers' knowledge) any surveys but especially those in remote and resource-constrained settings (Costenbader and Valente 2003). The appeal of indegree in practical applications is understandable because it directly reflects a basic quantity of interest and therefore its explanation is straightforward as opposed to complex network science algorithms behind other network metrics that can be easily misunderstood

(Wasserman and Faust 1994). Simple expressed in contemporary casual terms, indegree is the number of "followers".

The top 10% threshold corresponded to indegree of three or more (indegree is always integer by definition). This threshold reflects an old notion that "a person needs to be named by at least three other farmers to be regarded as possessing opinion leadership in the area of information sought by others" (Alamgir Hossain and Crouch 1992:p. 3). In exact terms, among the 2061 farmers in the network, 218 were named by at least three other peers as their sources of agricultural advice. Among these 218 farmers, one fifth (i.e., 43) were randomly filtered for the second stage of the selection process.

In the second stage, the Regional Manager of the implementing organization together with the Field Agent for Training and Coaching visited and interviewed these shortlisted farmers to explain the program and assess the potential participants' suitability and degree of interest in receiving coaching and acting as model farmers in the area for this program and further initiatives. Each visit lasted 45–60 min and less than half of the visited high-indegree farmers (18) were ultimately chosen for the role. The second stage interview process mimicked actual procedures conducted by the partner organization in their other programs to select participants based on consultations. As in other programs, any input and recommendation from field staff regarding the reputation or positive past collaboration with the farmer were also considered at this stage. The procedures followed in the second stage ensured that the selected 18 opinion leaders were found to be a good fit for the role by the program leaders and no one was selected to this role against their will. For comparison purposes, this selection was matched by a purely random selection of 18 farmers from a list of all 1843 certified cocoa farmers in the same district network whose indegree was less than three. There were no other considerations or steps involved in this mechanistic selection of the low-indegree farmers.

Analysis and feedback

First, t-tests and chi-squared test were used to compare the attributes of the opinion leaders with the low-centrality farmers and to compare the centrality of the opinion leaders who were selected in the interview process with the rest of the pool of high-centrality farmers from which they were drawn. Then, to test the hypothesis that involving intentionally selected central opinion leaders leads to a wider rapid impact on actions of others, t-tests and chi-squared tests were used to compare the number of adopters influenced by the two groups of participants week by week. Mann Whitney Wilcoxon test (which places weaker assumption on the distributions of the tested variables) was also performed and the outcomes were not qualitatively different. The distribution of outcomes of the two adopter groups was also compared in terms of variance to explore the consistency of impact among the identified opinion leaders and the random low-centrality farmers. Finally, correlation and OLS regression analyses of relations between the intervention participants attributes, centrality and their scale up impact were conducted.

The triggered number of adopters by different "seeds" tend to be highly skewed in networks and therefore these were analysed in their log forms (+ 1). This complies with the distributional assumptions of the employed statistical techniques and also the substantial notion that a difference of one additional adopter is considered relatively more substantial in lower ranges than higher ranges. Similarly, indegree was also used in the models in its log form (+ 1) because it is a naturally highly skewed network metric and because a difference of an extra follower is considered more substantial for individuals who do not have only few of them. In other words, an increase of followers or adopters from 0 to 1 is considered more substantial then increase from 50 to 51. Nevertheless, using the network metrics in their raw form or alternative measures of centrality (e.g. betweenness) did not qualitatively change the results. Other structural characteristics of networks were also controlled for in alternative OLS specifications (e.g. transitivity) but these were neither significant nor contributing to the model fit and therefore and are not included in the models presented here. All data analysis was conducted in R and network metrics were obtained using R package igraph (Csárdi and Nepusz 2006).

Previous research has demonstrated the usefulness of interpreting quantitative results of network analysis of social and ecological systems in light of qualitative information from the field (Labeyrie et al. 2019). The analytical results obtained from this experiment were presented back to the partner organization and feedback was obtained over five 1-h meetings and via follow up emails and reports from four organizers of the intervention who were in the field and from two farmer coaches. This opportunity was also used to obtain confidential reflections on the attributes and approaches of intervention participants who were unexpectedly effective in motivating their peers to take the recommended action. An overall summary of the obtained qualitative feedback is presented at the end of the result section and informs the subsequent "Discussion " section.

Results

As is common to many real-world social networks, the distribution of centralities among farmers in the advice network is skewed. Figure 2 visually illustrates a part of local social network structure in which a smaller number of high-indegree nodes is surrounded by numerous low-indegree nodes.

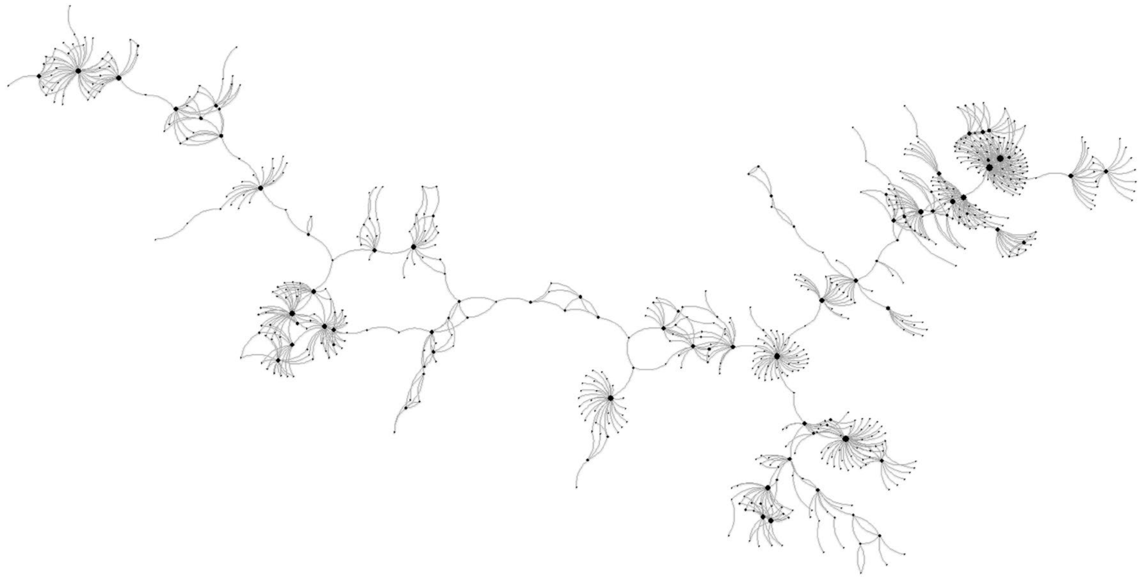

Fig. 2 The largest interconnected component of the certified cocoa farmers' advice network in the district. Each node is one cocoa farmer; node size reflects the number of advisees who named the farmer as their source of agricultural information; links represent the reported advice relationships between them

The distribution is statistically described in the Appendix. The analytical results presented in the following subsections shed light on which characteristics did identified opinion leaders tend to have in common (apart from their high centrality), how impactful were they compared to low-centrality farmers, and which other (non-network) characteristics predict scale up impact?

Opinion leaders' attributes

The farmers who were identified as opinion leaders tended to have some characteristics in common which distinguished them from the random low-centrality farmers (Table 1). The identified opinion leaders were significantly older than the random low-centrality cocoa farmers in the district (49 years versus 36 years, see also Appendix for distribution) and almost all were male (89% versus 66%). By definition and by design, they had higher centrality (indegree 16.9 versus 0.2). The appendix shows that the mean indegree of the 18 opinion leaders who were ultimately selected after the interviews is higher than the mean indegree within the pool of the candidates from which they were chosen. (In other words, the selected opinion leaders' indegree is higher than the mean indegree among all farmers in the district whose indegree

Table 1 Descriptive characteristics of the district network, the identified opinion leaders and the random low-centrality program participants

Measure	Full district network	Identified opinion leaders	Random low-centrality farmers	p-value
Number of farmers	2061	18	18	
Age (years)		49.2 (8.2)	35.6 (5.8)	p < 0.001
Gender (male = 1; otherwise 0)		0.89	0.66	p = 0.033
Completed secondary education (= 1; otherwise 0)		0.61	0.33	p = 0.835
Indegree (No. of "followers")	1.04 (4.17)	16.89 (16.04)	0.22 (0.55)	
Uptake in first week (No. of influenced farmers)		5.61	14.56	p = 0.059
Uptake in first 2 weeks (No. of influenced farmers)		8.61	17.06	0 = 0.107
Final uptake (No. of influenced farmers)		9.78 (10.32)	17.05 (19.38)	p = 0.175
Variance in final uptake		106.65	307.47	p = 0.013
Indegree of influenced farmers		2.66 (8.48)	1.71 (5.50)	p = 0.198

The p-values are for Welch two-sample t-tests of means of the two participant groups for continuous variables and McNemar's Chi-squared test for binary variables. Variances in uptake from central and peripheral farmers were compared by F test. Means followed by standard deviation values in parentheses are presented where applicable is at least three). Although this difference is not statistically significant (p = 0.135), that fact is that some of the farmers who passed the interview screening had a particularly high indegree. Based on the available network data, the participating low-centrality farmers seem statistically completely indistinguishable from the entire population of cocoa farmers in the district with indegree of 2 or less (mean indegree 0.2 for both the selected and the not-selected low-centrality farmers, p = 0.854), suggesting that the selection was indeed purely random as intended for this group.

Scaling up of intervention outcomes

Overall, the intervention diffused substantially through the participants' networks. Although the number of farmers directly involved in the program (36) was less than 2% of the eligible certified cocoa farmers in the district (2061), the intervention reached 24% of the district—in total 497 took the recommended action within 4 weeks of the intervention. However, comparing the impact of the opinion leaders and the low-centrality participants revealed results contrasting to the original assumptions and the intention of the program. Despite the additional effort in their selection and recruitment, the identified opinion leaders were clearly not more effective in convincing others to take the recommended action. In fact, they appeared less effective particularly in the beginning of the observed period. In the first week of the intervention, an average opinion leader influenced only 5.6 farmers, while an average random low-centrality farmer influenced 14.6 farmers to take the recommended action. The gap does not increase after the first week anymore and the outcome stabilizes at 9.8 influenced farmers for an average opinion leader and 17.1 farmers for an average random low-centrality participant (Fig. 3). This difference is not statistically significant in the 4th week anymore (p = 0.175) due to a large variation of outcomes for the non-opinion leader group.

Although the impact of opinion leaders was not higher than the impact of low-centrality farmers, their outcomes are more consistent. Each of the selected opinion leaders spread the message and influenced at least two other people. Among the non-opinion leaders there were two cases of no impact at all and some cases of exceptionally high impact. The difference in variance of outcomes between the two groups is statistically significant (p = 0.013, Table 1). For privacy and consent reasons, we do not have access to attribute data of farmers who did not directly participate in the intervention as "model farmers", only their network position and information regarding the recommended action. In this network data, we do not see a statistically significant difference between those who were influenced by the opinion leaders and by the random low-centrality farmers. Apparently, even the peripheral network members were able to influence some

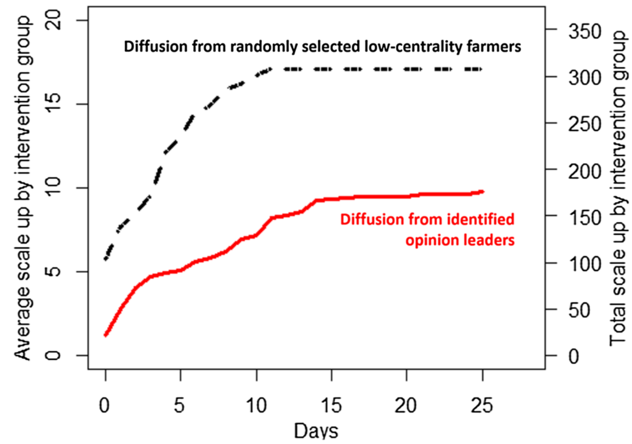

Fig. 3 Cumulative diffusion curves of the impact of the intervention on farmers taking the recommended action. The vertical axis shows the number of the farmers to whom the intervention has diffused through social networks and the horizontal axis shows the number of days since the start of the intervention

highly central network actors (including someone of indegree 43) and the status of these highly central actors did not prevent them from reporting the fact.

Correlates of intervention outcomes and participants' characteristics

Apart from the obvious correlation of being in the opinion leader category and indegree (because opinion leaders were defined and preselected based on their network centrality), the highest correlation coefficients between the intervention participants' characteristics are between: (1) age and being selected as an opinion leader (R = 0.702; p < 0.001); and (2) age and indegree (R = 0.683; p < 0.001). These are followed by correlation coefficients showing that (3) male participants had higher formal education and (4) indegree but (5) a lower impact on the immediate actions of others.

In other words, older more educated men were more likely to be nominated in network surveys by fellow farmers as the person to go to for agricultural advice and more likely to be confirmed by the staff of the implementing organization as suitable opinion leaders, but they were less likely to influence others into taking action during this intervention. The only statistically significant predictor of impact on others was being female (R = 0.333; p = 0.048).

Determinants of scaling up

The relationship between participants' gender and their contribution to multiplying the impact of the intervention is further examined here. Specifically, it is tested whether the effect of gender prevails after controlling for other participants' characteristics that may be to some degree associated with gender. The results of OLS regression show that the effect of gender is robust to various model specifications with any combinations of available controls (Table 3).

Among all tested specifications, the only other intervention participant characteristic with p-values close to a lenient threshold of significance of 10% is education (and education was lower for the participating women than men, see Table 2). No other effects were approaching this p-value threshold in any combination of any of the tested specifications. The first presented specification in Table 3 shows a model with all available (and clearly redundant) participant attributes included. Notably, intervention participants' network centrality seems to have no statistical association with their scale up impact ($p = 0.81$). This insignificant result prevails irrespective to transformations of the metric or substitution by any other popular network centrality metrics (such as betweenness). In model 2 (Table 3), when the positive impact of (generally male's) higher education is controlled for, the positive association of female gender with scale up impact is most pronounced ($p = 0.015$). This model specification appears to have the best fit of all tested specifications in terms of proportion of explained variance and size of residual standard errors.

Feedback from the field

The implementing organization considered the intervention to be a success in terms of its overall impact and the uptake of pruning but the finding that carefully identified opinion leaders did not have a higher impact than randomly selected low-centrality farmers was highly unexpected for the organizers. Upon reflection on the analytical results, several possible interpretations were provided by the staff of the implementing organization. It was considered that, although they were screened for suitability and willingness through interviews, the high-status opinion leaders possibly did not see this opportunity as something special because some of them had already been repeatedly engaged by external institutions and organizations operating in the district. The importance of the interviews in the selection process of the opinion leaders was repeatedly emphasised by the staff who did not find all sociometrically shortlisted individuals to be willing to go out of their way to help promote recommended agricultural practices to others. Also, some senior local social figures were reported by others as sources of agricultural advice apparently because of their prominent position in local organizations but in fact conducted little cocoa farming by themselves.

Table 2 Correlation of intervention participants' characteristics and outcomes with Pearson's R coefficients above the diagonal and corresponding p-values below the diagonal

	No of influenced farmers (log)	Age	Indegree (log)	Completed secondary education (= 1)	Male (= 1)	Opinion leader (= 1)
No of influenced farmers (log)		− 0.159	-0.101	0.122	− 0.331	− 0.103
Age	0.354		0.683	− 0.035	0.161	0.702
Indegree (log)	0.572	0.000		0.333	0.368	0.910
Completed secondary education (= 1)	0.480	0.840	0.054		0.372	0.278
Male (= 1)	0.048	0.349	0.032	0.026		0.267
Opinion leader (= 1)	0.550	0.000	0.000	0.100	0.115	

Table 3 OLS regression of number of influenced farmers (log) in relation to the characteristics of intervention participants who influenced them. Adj-R2 is computed using Wherry Formula (Yin and Fan 2001:p. 3)

	1			2			3		
	Estimate	Std. Error	p	Estimate	Std. Error	p	Estimate	Std. Error	p
Intercept	3.24312	1.07756	0.005	2.7147	0.363	0.000	2.7912	0.3691	0.000
Male (= 1)	− 1.10304	0.46397	0.024	− 1.1299	0.439	0.015	-0.8568	0.4185	0.048
Secondary education (= 1)	0.55218	0.41328	0.191	0.6116	0.365	0.104			
Age (Years)	− 0.01389	0.02726	0.614						
Indegree (log)	0.04949	0.20697	0.813						
N	36			36			36		
R2	0.1872			0.1793			0.1098		
Adj-R2	0.08232			0.1295			0.08357		
Residual standard error	1.045			1.017			1.044		

Nevertheless, the selected opinion leaders were still seen by the implementing organization as highly reliable and although they were not the seeds of the largest scale up impact, they were still considered as potential "show-stoppers" in future practical interventions if they were not involved. Although the unexpected outcome suggested that they were not the most pro-active promoters of the message of the intervention, the field coaches reported that most of the opinion leaders were a good cohort to coach because they demonstrated interest in new techniques. Even those who were originally assessed by the coaches as "late adopters" (three individuals) were found receptive to the intervention. One of them was quoted as saying that he converted to a pruning enthusiast through the program.

In contrast to the opinion leaders, the random low-centrality farmers have not had the experience of being treated as "model farmers" in the district and several of them seemed very keen to demonstrate their capacity to the partner organization and their peers. The organizers' retrospective interpretation of some socially less-prominent farmers' high engagement in the scaling up of the program was that they had relatively more to gain socially from telling others about the time-limited opportunity to gain a free piece of equipment. The organizers also noticed the younger participants' leveraging of social media and ICT communication (in particular messages via WhatsApp groups to which they had access) for spreading the message about pruning and the program. Finally, while geographical information is not a part of the anonymized dataset available for our research purposes, the organizers reflected upon the results that the truly randomly selected low-centrality farmers were not only on the social network periphery of the district but were also more dispersed geographically. Therefore, each purely randomly selected low-centrality farmer was typically the only one in their neighbourhood who participated in the intervention. Therefore, for each randomly selected low-centrality farmer, there was apparently a larger pool of geographically proximate potential adopters who were not directly included in the program as compared to the selected opinion leaders who were more geographically concentrated.

Discussion

Network effects do not manifest themselves in trivial ways and apparent social stars are not always as consequential in social diffusion processes as their visibly prominent positions in diagrams obtained from network surveys might suggest. Opinion leaders often occupy visible intermediary positions between formal and informal agricultural knowledge systems (Kabirigi et al. 2022; Teschner and Orenstein 2022). Network surveys aiming to capture perceptions of influence may be affected by opinion leaders' formal standing, such as farm group leaders, for example, that might not accurately reflect actual influence on others to take action. The risk of simplistic application of network research is that, powered by convincing visual depiction of networks, it may be used to justify less equitable and not always more effective resource allocation in rural development programs, such as to potentially already overloaded central network actors whose efficiency to convey information and influence might have diminished. However, when used cautiously, these analytical and communication tools can help to ensure that even socially peripheral pockets that would normally be missed are included.

Cautiously applied network mapping can be useful to corroborate local influencers and possible agents of change for sustainability initiatives (Andriamihaja et al. 2021). Even these central network actors do not end up promoting an external project, they may still need to be engaged as a matter of local cultural protocol or for political reasons to ensure they would not obstruct a project as the gatekeepers of the community. The present analytical results combined with feedback from the implementing staff suggest that engaging opinion leaders may be a feasible way to deliver a certain level of impact relatively reliably, if their suitability and willingness to be engaged has been confirmed. Nevertheless, social norms, traditions, cultural stereotypes and biases influence who is seen as a successful leading farmer (Walter 1995; Peters 2001). Studies from multiple societies have shown that men may be commonly perceived as the normative farmers ad opinion leaders mainly because of their vocal engagement within generally highly gendered division of roles in smallholder agriculture communities, while women's crucial contributions to agricultural production is less appreciated, less rewarded and less visible (Sachs 1983; Harcourt 2017; Wijers 2019; Quero-Garcia et al. 2017; Andersson et al. 2022). Specifically in Indonesia, access to education, patriarchal political, institutional and social norms combined with religious traditions have been pointed out as factors in socially marginalizing women in smallholder agriculture, which are often unintentionally further reinforced by international players that engage with local communities under these inequality regimes (Wijers 2019).

Relying only on the most locally visible and established figures may miss radical success potentially delivered by less-established others, often women and younger farmers, as well as farmers from the social and geographical peripheries of their communities. Although they may appear as uninfluential, they may have access to alternative informal networks and capacity that may not be recognized by the broad community, intervention organizers or researchers. Indeed, research in neighbouring Papua New Guinea has shown that women tend to have stronger information connectivity via close-knit networks with family and friends

(Friedman et al. 2022a, 2022b) but these may be missed in district wide sociometric surveys focused on identifying large-scale opinion leaders across broader social niches. On the other hand, individuals who are nominated as advice-givers and opinion leaders by their peers may be recognized as such mainly because of their locally accepted social status rather than real influence on their everyday practices and actions (Lazega and Montes-Lihn 2021). Figure 1 as well as the skewed indegree distribution statistics in Table 1 and the Appendix illustrate how farmers in this district often remarkably agree of who the important advice givers are (in the case of the most popular opinion leader, 71 farmers named him as their source of advice) but the reality of who is proactive, technologically capable and has actual impact on others' immediate actions might be different.

Being involved in an international program and having the opportunity for the first time to raise their status within the community in this way seemed to encourage more active engagement of several participants. As elsewhere these days (Skaalsveen et al. 2020; Munthali et al. 2021; Rust et al. 2022), online communication platforms played a strong role (although this was not a deliberate part of the experiment design). When given this rare opportunity, some motivated young farmers were able to leverage virtual networks even if they were possibly accessing these from positions on the periphery of the community networks. This outcome might be considered a placebo or a Hawthorne effect, in other words, an effect of being involved in an experiment and being observed that leads to improved performance by those who were not used to such situations. Even if it is a placebo effect, it is one that seems to work and presumably could be replicated by intervention organizers elsewhere too.

The presented results should not be interpreted that networks do not matter. Afterall, the intervention evidently scaled up through networks of the 36 program participants to 497 adopters within 4 weeks. Networks and central network position may sometime matter more visibly for blocking social diffusion than facilitating it. From theory of complex contagion, central network actors may be more effective in preserving status quo by diffusing what is in line with the status quo rather than changing it by diffusing something new. In some cases, central network actors may provide more effective opinion leadership in terms of resisting change than for promoting it.

Especially in centralized communities, leaders can have disproportional influence in preserving the status quo (Matous and Bodin 2021), so investing in their identification and winning their hearts and minds may be justified. However, exclusively selecting only farmers in already privileged social positions (who are often senior men) for a priority access to novel technologies and resources before anyone else is ethically questionable. It is also ethically dubious to necessitate for other farmers (who are not senior men) to rely exclusively on these high-status individuals to access external program benefits, such as valued knowledge, material inputs or financial subsidies, and thus entrench extent power differentials (Taylor and Bhasme 2018). When this approach seems most instrumentally effective for achieving large-scale impact, it is an ethical dilemma how to balance it against the considerations of equity. It is the perceived power and social authority that attracts extension agencies, international development organizations and private profit-seeking enterprises to these farmers (Taylor and Bhasme 2018). However, the predominant approach of selecting opinion leaders seems to be based more on untested intuition, studies in other domains and convenience rather than evidence from agricultural context. This experiment illustrates that targeting (often senior male) opinion leaders is not necessarily always the most instrumentally effective approach and that less recognized farmers (such female and junior farmers) can proactively and effectively support intervention programs even if they are not conferred central social status within their community and their potential is readily noticed by external institutions. Although international development agencies and public sector organizations have officially recognized the need for addressing gender equity in their programs, the tendency to travel the path of least resistance by consolidating established networks of male farmers and building on the hierarchies they dominate generally prevails (Taylor and Bhasme 2018).

Another important consideration is that the way someone's relationships are structured may matter more than the number of their relationships. Indegree, i.e., the number of "followers", can be considered a "vanity metric" that may make someone look important but has less practical impact than a metric that considers the reach of these links across local social structures (Sutherland 2022). When sociometric data is available, targeting interventions by other metrics than the sheer number of nominations by others, for example metrics that quantify the farmers bridging across social divides and diverse network cliques may be more effective (Zhang et al. 2020). However, the sample of participants in this intervention was quite small and stratified by indegree only. The intervention was not designed to assess the nuances of different ways of being central in a network. For example, the three most impactful intervention participants all happened to have zero links, which translates to zero centrality by any network metric, however sophisticated it may be. Moreover, in practice full network metrics are normally not available. Fortunately, other network intervention approaches that do not require such structural information and do not involve identification of high-centrality individuals have recently shown great promise, for example, by targeting pairs of random individuals together with their nominated friends (Alexander et al. 2022).

It is also necessary to acknowledge that this study assessed only on one type of intervention (and different types of interventions might be difficult to test realistically and rigorously without diverging too much from their real format and implementation on the ground). Promoting a relatively simple and costless action does not probably require the perceived expertise or status that more ambitious interventions might. Depending on context and the type of intervention, farmers may in some cases depend more on their own local social niche and in other cases on perceived district "expert farmers" with higher levels of perceived experiential knowledge, higher epistemic legitimacy and higher centrality across wider social niches (Skaalsveen et al. 2020; Lazega and Montes-Lihn 2021).

Conclusion

Farmers often view each other as their main sources of advice and draw on their personal networks to share knowledge and enhance their adaptive capacity (Skaalsveen et al. 2020; Kabirigi et al. 2022). Well-targeted network intervention programs at their best provide a promise to deliver large-scale adaptive responses to environmental changes and sustainability challenges of agricultural systems by leveraging these relationships (Kabirigi et al. 2022). Interventions are also a source of data for better understanding of causal processes within agricultural systems, which cannot be clarified from purely observational studies that do not intentionally alter the system elements.

The selection of participating farmers in such programs is consequential. Organizers of intervention and scaling up programs need to ensure that by focusing on reaching numbers of adopters at the end of their project do not cause more harm than good (Woltering et al. 2019), especially when following the popular approach of delivering these programs via model farmers selected based on their capacity and perceived local influence (Taylor and Bhasme 2018; Wairimu et al. 2016). This is a long known issue that does show signs of improvement (Röling et al. 1976). Long-term side effects such overreliance on individuals in prominent positions may have on the community social networks and its resultant ability to perform adaptively and equitably in the face of environmental change are a concern. Providing additional resources exclusive to high-status model farmers can exacerbate the dynamics of local social differentiation with unintended consequences (Taylor and Bhasme 2018; Isaac et al. 2021) as social and structural impacts of such programs typically go hand in hand and jointly affect the sustainability and resilience of rural areas (Junquera et al. 2022).

The present analysis further calls for attention to (often gendered) biases that may be present in identifying opinion leaders. Assessing model farmers' opinion leadership based on their centrality (or more likely by its cost-effective proxies that ask for nominations of influential farmers from only several arbitrary community members or field workers) can be one part of the process but it needs to be remembered that it may be clouded by stereotypes and prejudice. Managers and policy makers should also explicitly consider how their intervention could be a vehicle for social network transformation and creation of collaborative social capital for those who lack it (Wu and Zhang 2013). Involvement in public programs as model farmers can build participants' prestige which they can turn into other attractive engagements (Taylor and Bhasme 2018). The present case shows that providing more opportunities to underrepresented groups among model farmers may be justified not only the grounds of social justice, which I would consider a worthy end in itself, but even on the grounds of immediate quantifiable instrumental impact—the type of KPI that implementing institutions are often (unfortunately) predominantly driven by (Woltering et al. 2019). Women may in general play different roles from men in agricultural systems in various societies (Friedman et al. 2022) and in this program women performed notably well in terms of the immediate dissemination of the intervention's message although they did not tend to be identified as opinion leaders in the local agricultural advice networks. Another outcome of the experiment that is worth mentioning is the evidently effective utilization of social media and online communication tools by some younger farmers to spread the message of the intervention, confirming the potential power of these channels in remote rural contexts.

In terms of the first step of Lazarsfeld and Katz's model introduced in the beginning of this paper, the experience shared by the field coaches in this program serves as a reminder that the most central network actors are not interested in or suitable for tasks intervention that organizers want them to do. Being socially central (especially in a conservative community) does not mean being progressive, interested in sustainability of agricultural systems, engaged in practice in the task in focus or easily influenced by external actors to put once valued high social standing on the line for their programs (Alamgir Hossain and Crouch 1992). Older farmers are often referred to for advice but they are not necessarily interested in novel technologies or conservation practices (Parks 2022; Prokopy et al. 2008). Opinion leaders normally hold locally mainstream centrist views that *reflect*, but do not necessarily *lead* or *change*, the opinions of their communities (Shrestha et al. 2004; Han et al. 2021). In this intervention, interviews were conducted to confirm the willingness of the sociometrically preselected opinion leaders to contribute towards positive change in local farmers' practices, which proved indispensable but not fully sufficient. Being a recognized model farmer may come with frequent requests for collaboration in programs run by external organizations, and while local opinion leaders may still agree to participate for various reasons, including the usual associated benefits in terms of "enhanced social status, networking, material transfers and opportunities for further income generation" (Taylor and Bhasme 2018:p. 3), the eagerness to prove oneself may gradually diminish and influencer fatigue take over.

At the second step of the two-step model, even when opinion leaders do what they were expected to do, they might not be the best ones to seed interventions due to social network topology. The limitations of central network influencers have been explored in other contexts and explained in the theory of complex diffusion (Centola 2021). The experiment reported here illustrated in the context of remote communities that even individuals who have been reported by numerous peers as important sources of agricultural information are not necessarily more effective conduits of agricultural programs than random low-centrality farmers. This adds to concerns raised in other studies that external interventions, especially when implemented through central actors, may further promote network centralization of the targeted agrarian communities and that consequently positive change may be harder to come by in more centralized communities (Heß et al. 2021; Matous and Bodin 2021). The imaginary trickle down model of influence flowing vertically down from those who are more educated, better off and significantly more prominent rarely works in practice (Feder and Savastano 2006) and engagement of highly central influencers can often backfire (Centola 2021). Selecting model farmers that truly represent the composition of the intended population, including harder-to-reach groups, can be not only more equitable but sometimes even more effective. The original two-step model already recognized that people who have true influence tend to be very much like those whom they can influence, only more exposed to the points of contact to the outside world (Katz 1957).

Network interventions come with high ethical responsibility. Donor-funded interventions may aim to foster environmental sustainability through better technologies and practices applied at the farm level, while unintentionally reinforcing centralized and unequal social systems that obstruct adaptive community social processes necessary for sustainable and just development at the societal level. Planners and managers of agricultural system interventions need to minimize the risk of aggravating local inequalities and hampering the effectiveness of their programs by excessively focusing on local central actors and further increasing the local power differentials by elevating those who are considered to be the local elite already (Rockenbauch et al. 2019). Achieving impact at scale is not just about reaching high numbers of intervention adopters at the end of the project timeline (Woltering et al. 2019). Fundamentally, it is about strategically altering system structures to enable positive change. One of the ways to do that may be by providing marginalized and socially peripheral community members opportunities to create social capital and to gain transformative agency that would enable them to drive change from the peripheries of their communities.

Finally, it is worthwhile reiterating that interpersonal influence via social networks is of course never the only factor behind farmers' adoption or non-adoption of recommended practices. Holistic intervention programs naturally need to consider not only networks but also other potentially larger barriers of scaling up of agricultural intervention programs, including geophysical variables of each locale, economic factors, supply chain constraints, and farmers' deeper life values such as environmental attitudes that are not always likely to change in response to their social networks (Thompson et al. 2015; Reimer et al. 2012; Peterson et al. 2022; Knowler and Bradshaw 2007). Any improved development program delivery model should consider these factors and social networks in conjunction.

Appendix

See Table 4, Fig. 4.

Table 4 Degree distributions

	N	Minimum	Median	Mean	Maximum	Standard deviation
All farmers' indegrees	2061	0	0	1.33	71	4.57
Identified opinion leaders' indegrees	18	3	13	16.89	71	16.04
Randomly selected low-centrality participants' indegrees	18	0	0	0.22	2	0.55
Nodes with indegree > = 3	218	3	8	10.88	71	9.68
Nodes with indegree < = 2	1843	0	0	0.198	2	0.49

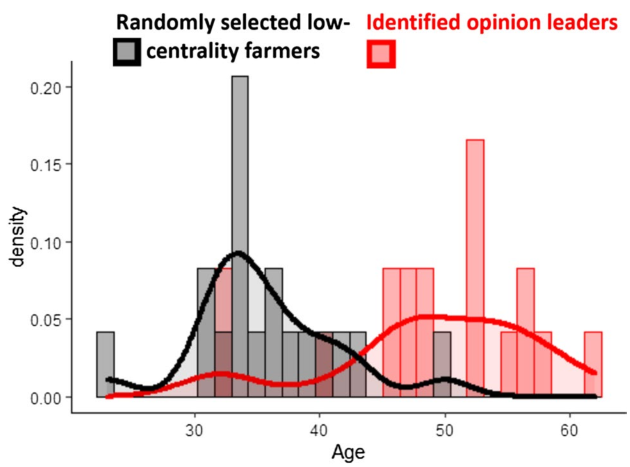

Fig. 4 Intervention participants' age distribution by group with a kernel density estimate

Acknowledgements I would like to thank Swisscontact, in particular Ross Jaax, Christina Rini, Hiswaty Hafid, Rina Islamiyati and Teuku Bahran Basyiran, for implementing the project and for sharing the outcomes together with their invaluable experience. I am also grateful to Sydney South East Asia Centre for supporting this research and to colleagues who have given me advice on this study.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions. This study was supported by Sydney Southeast Asia Centre, University of Sydney.

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Petr Matous is an Associate Professor at the University of Sydney. Petr teaches innovation and sustainability and researches the interplay between social networks and development programs in rural areas and marginalized communities with a particular interest in smallholder farming in South East Asia.