

1 **Combining simulation and empirical data to explore the scope for social network interventions in**
2 **conservation**

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Abstract

Conservationists can use social network analysis to improve targeting for behaviour-change interventions, selecting individuals to target who will go on to inform or influence others. However, collecting sociometric data is expensive. Using empirical data from a case study in Cambodia and simulations we examine the conditions under which collecting this data is cost-effective. Our results show that targeting interventions using sociometric data can lead to greater dissemination of information and adoption of new behaviours. However, these approaches are not cost-effective for small interventions implemented in only a few communities, and it is an order of magnitude cheaper to achieve the same results by simply targeting more individuals in each community at random. For interventions across multiple communities, network data from one community could inform rules-of-thumb that can be applied to boost the effectiveness of interventions. In rural Cambodia, this approach is worthwhile if it can inform interventions covering at least 21 villages. Our findings provide a framework for understanding how insights from network sciences, such as targeting clusters of individuals for interventions that aim to change behaviour, can make a practical contribution to conservation.

Introduction

Conservation interventions aiming to influence human behaviour commonly directly target the people they aim to influence (Jones *et al.*, 2019). An alternative perspective recognises that new behaviours tend to spread through social ties (Centola, 2018; Rogers, 2003), suggesting interventions should target influential individuals who subsequently propagate the behaviour throughout the group (Valente, 2012; de Lange, Milner-Gulland & Keane, 2019). This approach is rare in conservation, perhaps because collecting sociometric data to identify such individuals can be costly (Eckles *et al.*, 2019). A potentially cheaper approach is to use ‘rules-of-thumb’, or indicators of social influence (Valente & Pumpuang, 2007; Mbaru & Barnes, 2017), but little research has been done to identify such indicators in conservation. We use data from a case study in Cambodia to a) determine the cost-effectiveness of targeting informed by sociometric data, and b) explore the potential for identifying effective rules-of-thumb.

Little information is available about how conservation behaviour change interventions are targeted in practice, but much research has been devoted to identifying individuals or groups whose behaviour needs to be changed, or who are susceptible to change (Jones *et al.*, 2019), such as identifying frequent consumers of wildlife products, or those willing to adopt alternatives (Doughty *et al.*, 2019; Davis *et al.*, 2016). This suggests targeting based directly on observations of the behaviour that the intervention aims to change. However, many behaviours spread through less easily identifiable social processes such as communication and conformity, which may be unrelated to the behaviour of concern (Borgatti *et al.*, 2009; Centola, 2018; Rogers, 2003). For example, bushmeat hunting in the Amazon is often driven by affective relations between friends and kin (Carignano Torres *et al.*, 2021). Understanding the social relationships within a group can therefore suggest ways to more effectively target an intervention (Valente, 2012; de Lange, Milner-Gulland & Keane, 2019).

55 Sociometric data (i.e. data about social ties) can enable researchers to identify an optimal set of
56 target individuals to maximise the spread of new behaviours or information (Banerjee, Jenamani &
57 Pratihari, 2020). A common approach is to target so-called 'key-players' using measures of
58 importance in a social network (Valente & Pumpuang, 2007; Borgatti, 2006), such as those that have
59 the highest number of connections with others (referred to as *in-degree centrality*). Randomised
60 controlled trials in various contexts have shown that targeting interventions at key-players can lead
61 to greater adoption of new behaviours compared to other approaches (Kim *et al.*, 2015; Paluck,
62 Shepherd & Aronow, 2016; Valente, 2012).

63 However, to robustly identify key-players spanning a network, it is desirable to have sociometric
64 data covering as much of the target population as possible (Knoke & Yang, 2011; Borgatti, 2006;
65 Costenbader & Valente, 2003). In conservation contexts, which are often rural, remote, and low-
66 technology environments, collecting such data requires costly surveys (Eckles *et al.*, 2019). A
67 potentially cheaper way to identify key-players is to use proxy attributes thought to correlate with
68 influence, such as wealth, experience, or formal leadership positions (Valente & Pumpuang, 2007).
69 For example, Mbaru & Barnes (2017) used sociometric data from fishing villages in Kenya to
70 determine that formal leaders, but not experienced fisherman, tended to be key-players. Therefore,
71 targeting formal leaders could be a rule-of-thumb for better targeting within similar contexts.
72 However, such rules-of-thumb are not universal (Valente & Pumpuang, 2007) and in some contexts
73 suitable rules-of-thumb may simply not be identifiable (de Roo *et al.*, 2021).

74 Despite the effectiveness of key-player targeting, approaches based on individual network positions
75 may be insufficient when the adoption of behaviours depends on social reinforcement (Centola &
76 Macy, 2007; Aral & Walker, 2012). The spread of these behaviours is referred to as "complex
77 contagion" and exhibits different patterns to the spread of "simple contagions", such as information,
78 which can spread easily through single exposures (Centola & Macy, 2007). For individuals to adopt
79 "complex" behaviours, multiple social peers need to adopt first, meaning a single key-player may not

succeed in promoting adoption while interventions can better target clusters of mutually connected individuals (Centola, 2018). For example, rather than targeting two key-players in different parts of a network, targeting a key-player and one of their peers will enable them to collectively influence their mutual acquaintances (Centola, 2018; Beaman *et al.*, 2014).

For conservation practitioners to be able to target their interventions most effectively, we need to understand the cost-effectiveness of using sociometric data, and the possibility of identifying rules-of-thumb, across different intervention contexts. We combine empirical and simulation approaches within a case study from Cambodia to make two contributions: First, to evaluate the relative cost-effectiveness of strategies informed by sociometric data and theory at spreading information or behaviours under different conditions, compared with conventional targeting strategies. Second, to identify rules-of-thumb that might be used to identify key-players and target interventions more effectively in this context. We use data from the case study and a range of strategies to generate sets of individuals to target for intervention and compare the composition of these sets to identify possible rules-of-thumb. We then use diffusion simulations to predict the effectiveness of these different targeting strategies and compare their relative cost-effectiveness.

Methods

Case study

We use data from a village located in a protected area in northern Cambodia, situated near critical wildlife habitat and involved in several long-term conservation initiatives, including a bird-nest protection scheme, a conservation agriculture programme, and community forestry, overseen by separate elected village committees (Poffenberger, 2013; Clements *et al.*, 2010). Most village households are engaged in rice-growing as a primary livelihood. The village has a chief and sub-chief appointed by the state. Furthermore, environmental education and conservation awareness-raising events are regularly implemented.

Currently, conservationists and residents are concerned about cases of wildlife poisoning that have been documented in the surrounding area. One intervention being trialled by the Wildlife Conservation Society and local authorities is the introduction of a hotline for reporting poisoning (de Lange *et al.*, 2020). To promote the hotline, it is necessary to both widely disseminate information about the hotline (e.g. the phone number, the purpose of reporting), and to help residents overcome concerns they may have about social conflict or disapproval from others (i.e. social barriers). An intervention might thus target individuals well positioned to disseminate information, or target in a way that maximises the social reinforcement needed for widespread adoption of the hotline to occur.

Data collection

We collected data using questionnaire surveys at two time points. All questionnaires were previously piloted and refined with individuals in another village and were translated from English to Khmer and back to check accuracy. They were conducted in Khmer using tablets and Open Data Kit software (Brunette *et al.*, 2013). In September 2017, we aimed to interview all consenting adults in the village and recorded sociometric and demographic data. We recorded respondent's age, occupation, positions in the village. We measured household wealth using a Basic Necessities Survey previously developed for this region (Beauchamp *et al.*, 2018). In January 2019, after the intervention objectives were established, we interviewed a further sample of households to measure attitudes related to reporting of poisoning. We interviewed all adult residents of 93 randomly selected households (~60% of households, 155 individuals in total). We measured attitudes using four five-point scales, which were then summed to produce an attitude score out of 20 (see Supplementary Material, SM4), as an indicator of the likelihood that an individual would adopt use of the hotline. All analysis was conducted in R 4.0.0 (R Core Team, 2017).

Social networks

To better understand social interactions and identify relevant ties, we first conducted qualitative research and consulted local experts (SM1). We then measured a habitual social contact network, which captures the relations through which residents are likely to communicate about the intervention. In rural Cambodia, the household forms the core of social organisation, (Ovesen, Trankell & Ojendal, 1996), and individuals within a household likely spend significant time together and share information about many topics. Outside of the household we identified household visits as an important form of interaction. We asked respondents to nominate others that they have regularly visited at home in the past year. We allowed respondents to freely recall as many names as they wished and prompted them until they declined to nominate further.

We checked the sociometric data for misspelled names using three procedures (SM3), then constructed the social network by including directional household visit ties (i.e. if person A nominates person B as a social contact, then information can only flow from B to A), and bidirectional household co-residence ties, assuming homogenous mixing within the household (SM2).

Intervention targeting

We identified plausible targeting approaches, based on the literature and on our own experiences, and selected sets of individuals to target for intervention following each approach. We selected sets of $n=2, 10, 20$, and 30 individuals to target, varying intervention effort to reflect the range of intervention intensities we have observed carried out by WCS Cambodia in this context, where directly reaching more than 30 individuals at one time is challenging.

Sociometric targeting

Using sociometric data, we identified sets of key-players in the network, using the centrality measures used by Mbaru & Barnes (2017): in-degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality (Table 1). We used the Keyplayer algorithm, which selects a set

of individuals that optimally span the network based on the centrality measures selected (Borgatti, 2006). Since our network has disconnected sections, we used the harmonic measure of closeness centrality.

We also generated clusters of connected individuals, which are predicted to better enable the spread of complex contagions. We used sociometric data to pair each key-player with one of the social peers whom they visit outside the household. For example, to generate a set $n=30$, we selected 15 key-players and 15 of their social peers.

Non-sociometric targeting

We identified non-sociometric targeting strategies currently used by conservationists through a literature search (SM5). This process resulted in nine commonly deployed and clearly definable targeting strategies (Table 2). For each strategy we selected sets of target individuals, using the demographic and attitudes data. The leadership and conservationist sets were not employed for effort level $n=30$, as there were not enough individuals meeting the criteria.

As a null comparator we also generated 30 sets of randomly selected individuals at each level of intervention effort. Furthermore, we created random sets of clusters, selecting random individuals, and a social peer for each. For example, to generate a set of size $n=30$, we selected 15 random individuals and selected 15 social peers.

Identifying rules-of-thumb

To identify rules-of-thumb we compared the composition of sociometric and non-sociometric sets using the Jaccard similarity index (Jaccard, 1912). This is the proportion of individuals that occur in both of a pair of sets. We also used binary logistic regression to assess proxy attributes correlating with each of the four key-player sets (at $n=30$), namely wealth, leadership position, age, and gender.

Comparing effectiveness using simulation

To examine the relative cost-effectiveness of each targeting strategy for diffusing information and behaviour change (simple and complex contagions respectively) at varying effort levels, we simulated diffusion of knowledge or intention to use the reporting hotline (hereafter: the contagion) through the network using the model specified in Dobson *et al.* (2019).

This model simulates diffusion of the contagion through a network based on simple rules. At any time, individuals (i) in the network have either received information or adopted a behaviour (i.e. the contagion, $\beta_i = 1$), or they have not ($\beta_i = 0$). Initially, at $t=0$, we assume that $\beta_i = 0$ for all individuals, except for those targeted for intervention, for whom $\beta_i = 1$. At subsequent time points ($t=1, 2, \dots, 20$) individuals are exposed (α) to the contagion through their network connections with others in their own household (X) or among those they visit (Y). Exposure through visits ties is weighted double, as we assume that social peers explicitly nominated are likely to be more influential on an individual's behaviour than household co-residents. Furthermore, stochasticity was introduced into the model through a 'communication probability', L : the probability that communication will occur following interaction between any pair of individuals at t , where $L = 0.2$ or 0.8 . Therefore:

$$\alpha = L(\sum \beta_x + 2 \sum \beta_y).$$

We used each of the sets of targets to initiate diffusion. Further individuals will adopt the information/behaviour ($\beta_i = 0 \rightarrow 1$) if $\alpha \geq \lambda$, where λ is the exposure threshold. To compare the spread of information with the spread of behaviour, we repeated the simulations with $\lambda = 1, 3$. At $\lambda=1$ information can be passed from any single connection, while at $\lambda=3$, at least two connections outside the household are required for adoption of the behaviour, or three within the household, or some combination of these. Each simulation continued until $t=20$ and was repeated 20 times. Each time step represents an arbitrary period, during which individuals may communicate with their peers.

As a measure of intervention effectiveness, we recorded the area under the diffusion curve (AUC, SM6), and calculated this as a percentage of the maximum possible AUC (size of network x number of periods). The AUC percentage reflects both the number of adopting individuals and the speed with which this change occurs. We calculated bootstrapped 95% confidence intervals across the 20 repeated simulations. For the clustered and random strategies, we combined results across all 30 sets giving 20x30=600 model simulations for each. We bootstrapped 95% confidence intervals for AUC across all 600 results.

Relative cost-effectiveness analysis

We estimated the financial costs of collecting the data required to identify targets for each strategy and to implement the hotline intervention, based on our experience (Table S6). The intervention takes the same format regardless of strategy, and cost is dependent only on the level of effort (i.e. the number of targets). This included travel, staff, and materials costs. For example, an intervention with two targets consists of two NGO staff meeting targets at their home and providing information materials. For interventions with twenty or thirty targets, multiple staff would take multiple days to prepare a venue, invite participants, and source additional materials, such as posters to display.

We summed the data-collection and intervention costs for each simulation and then linearly interpolated the cost required to arrive at a target AUC (using the 'approx' function in R). Assuming we can use our data to identify general rules-of-thumb applicable in other villages, we calculated the number of villages (N) an intervention must include for sociometric data collection to be cost-effective at achieving the target AUC. To do so, we used the formula $N = \frac{D}{C_{non} - C_{net}}$, where D is the cost of collecting sociometric data (\$5160), C_{non} is the cost of the best performing non-sociometric strategy, and C_{net} is the cost of the best performing sociometric strategy. This assumes that the increase in efficacy and effort required remains proportional across villages.

Results

Description of the sample & network

The network included 365 adults from 155 households: approximately 91% of all resident adults. The final habitual socialisation network included 1350 ties (see Table S1 for descriptive statistics).

Set comparisons & rules-of-thumb

Overall, targeted sets under different strategies were distinct and had little overlap (see Tables & Figures S2, S3 & S4). Of the key-player sets, only closeness and betweenness centrality had overlap with non-sociometric sets (albeit low; *Jaccard* = 0.05), namely with the wealth and gatekeeper sets respectively. At the highest effort level, the greatest overlap between a key-player set and a conventional set was $J = 0.09$ for the gatekeeper and in-degree centrality sets.

In-degree centrality key-players tended to be older (effect size = 0.52 ± 1.74 , $p = 0.003$), while closeness centrality key-players tended to be younger (effect = -0.80 ± 0.29 , $p = 0.005$). For eigenvector centrality, women were more likely to be included than men (effect size = 1.05 ± 0.45 , $p = 0.02$). No other significant correlations were found.

Simulations

Diffusing information

For diffusing information, all strategies performed well, and there was diminishing return on effort (Figure 1). At higher effort and higher communication probability there was low variation in performance. For example, at effort $n=30$, even the worst-performing strategies achieved >80% AUC. Only sociometric strategies performed significantly better than random targeting. In-degree centrality and betweenness centrality key-players performed best at all levels of effort, and clusters based on these two centrality measures also performed well. The best-performing conventional strategies were targeting through the gatekeeper and targeting those with less positive attitudes. These performed at the upper end of the random range. Other strategies performed similarly or worse than the median random strategy.

Diffusing complex behaviours

For the diffusion of behavioural changes (complex contagions), performance was lower and tended to increase linearly with effort (Figure 1). At low effort, only clustered strategies achieved diffusion. Variation in performance increased with effort and communication probability. For example, at the highest effort level and communication probability, the median random set achieved 18% AUC while targeting clusters based on the in-degree centrality key-players achieved 62% AUC. This was the best performing strategy, and the only strategy to perform better than random at all levels of effort. At $n \geq 20$, targeting in-degree, betweenness or eigenvector centrality key-players also performed well (Figures 1 & 2). Targeting clusters based on these key-players performed at the upper random range or better. Of the conventional strategies, only targeting through the gatekeeper performed better than random, at any effort level. Targeting wealthy households performed at the upper limits of the random sets at high efforts ($n > 20$, Figure 2). At low communication probability, targeting random clusters performed better on average than targeting random individuals.

Relative cost-effectiveness analyses

Intervention costs increased from \$52 for targeting two individuals to \$502 for targeting 30 individuals (Table S5), though the cost per person targeted decreased. Data collection costs were an order of magnitude greater: \$5160 for sociometric data, and \$2200 for other data (Table S6).

It was always more cost-effective to increase intervention effort and apply a conventional strategy than to collect data for sociometric strategies, or other strategies requiring data (i.e. people with less positive attitudes, wealthy people). For example, to achieve AUC=15% for a complex contagion at low communication probability, it would cost approximately \$318 using the gatekeeper strategy, \$487 through random targeting, or \$5276 for the best-performing sociometric strategy (in-degree clusters) (Table 3).

Targeting clusters based on in-degree centrality key-players was the best performing strategy for diffusing behavioural change, but was not cost-effective compared to other approaches. The cost of

sociometric data collection in this village to identify rules-of-thumb would be justified if used to inform interventions in thirty-one villages. To cost the same as a randomly targeted intervention only twenty-one villages are needed. For the diffusion of information, betweenness centrality key-players were most effective. To achieve 80% AUC at a comparable price to random targeting, the intervention must include 15 villages, but to achieve 70% AUC at comparable price to random targeting, 75 villages are required.

Discussion

Our results confirm predictions from network theory (Mbaru & Barnes, 2017; Valente, 2012) and evidence from other disciplines (Paluck, Shepherd & Aronow, 2016; Kim *et al.*, 2015) showing that sociometric targeting is more effective at diffusing new behaviours than non-sociometric strategies. In particular, targeting connected clusters of individuals is a highly effective strategy for diffusing behavioural change (Centola, 2018; Beaman *et al.*, 2014). Therefore, efforts to promote a poisoning hotline in this village should focus on communicating with identified in-degree key-players and their social relations. However, our results also show that, it is not cost-effective to collect sociometric data when the costs associated with collecting data are high compared to the cost of the intervention itself, and that resources would have been better spent on targeting more individuals. The value of sociometric data increases as diffusion becomes more challenging (Akbarpour, Malladi & Saberi, 2020). It was relatively straightforward to effectively diffuse information (a simple contagion): by targeting 30 random individuals it was possible to reach over 80% of the 365 villagers in our case study. However, when adoption of a behaviour requires social reinforcement or when the probability of communication between individuals is lower, targeting choices become more important. Within the range of interventions simulated, only sociometric targeting achieved diffusion of behaviour greater than 20% of the theoretical maximum. For sensitive behaviours such as wildlife poisoning, the probability of individuals communicating about the behaviour may be even

295 lower than we have modelled and is sensitive to social influences (de Lange, Milner-Gulland &
 296 Keane, in press), so we are likely underestimating the importance of effective targeting.

297 Although sociometric strategies were more effective at diffusing complex behaviours, it was an
 298 order of magnitude cheaper to target more people selected using a conventional strategy than to
 299 target a smaller number of key-players using sociometric data, as suggested by other simulation
 300 studies (Akbarpour, Malladi & Saberi, 2020). However, it may be worth collecting sociometric data if
 301 this one-time investment could be leveraged to generate rules-of-thumb that can be applied to
 302 improve intervention outcomes beyond the study site, or to inform multiple interventions in the
 303 same village (bearing in mind the dynamic nature of social networks). According to our analysis, this
 304 approach would become cost-effective if it could be applied across 21 villages (compared to random
 305 targeting and assuming the rule-of-thumb performs equally well as the sociometric strategy). For
 306 costlier interventions requiring prolonged engagement with targets (e.g. a farmer field school), or
 307 substantial financial incentives, collecting sociometric data will be relatively more cost-effective
 308 (Akbarpour, Malladi & Saberi, 2020) and formal analyses of the value of information could be used
 309 to guide decision-making around data collection (Canessa *et al.*, 2015).

310 However, our analyses did not identify any particularly promising rules-of-thumb, with much smaller
 311 correlations than those found by Mbaru & Barnes (2017). As in other studies in rural developing-
 312 country contexts, our results suggest that central individuals in the network are not necessarily
 313 those with the highest wealth or formal leadership roles (de Roo *et al.*, 2021). Nevertheless, at
 314 higher effort levels there was some overlap between the gatekeeper and in-degree centrality key-
 315 player sets. The gatekeeper strategy also performed relatively well in our simulations, indicating that
 316 using the village chief (the gatekeeper) to access and target other community members may be the
 317 most effective rule-of-thumb. Furthermore, our results probably underestimate the power of village
 318 chiefs (the gatekeepers in our case study) for diffusing behaviours as they can access further
 319 resources, networks, and use their social capital to reach others (Ledgerwood & Vijghen, 2002;

Marston, 2011). For example, we know that some village chiefs have organised meetings on their own initiative to discuss the issue of wildlife poisoning (de Lange *et al.*, 2020). Replicating our study in other villages or using qualitative local knowledge could provide confidence that this strategy is effective across rural Cambodia. An assessment of the best approach also needs to take other social and ethical considerations into account. For example, interventions working through gatekeepers may lead to elite capture of the benefits of the intervention, further marginalising other groups (Lucas & Lucas, 2016).

When sociometric data have already been collected, diffusion simulations can be applied to select optimal sets of intervention targets (Beaman *et al.*, 2014; Banerjee *et al.*, 2013). Our approach provides a framework for achieving this but could be refined to better capture real world dynamics. Firstly, individuals vary in their contribution to conservation behaviours (e.g. in consumption of wildlife), and could be weighted to reflect this. Secondly, one could use behavioural data to parametrise a distribution of adoption thresholds (Valente, 1996), reflecting the varying propensities of individuals to adopt new behaviours. Thirdly, one could include more tie types in a multiplex network to better capture the dynamics of social influence and information sharing. Fourth, our model output, the area under the diffusion curve, captures both the speed and the extent of diffusion. If intervention objectives require behaviours to diffuse within a particular timeframe, simulations can examine the performance of these parameters separately (Akbarpour, Malladi & Saberi, 2020). Finally, future research should exploit the development of new network measures, which are being developed to better identify individuals best placed to diffuse complex contagions while taking into account wider network structures (Guilbeault & Centola, 2021).

When more complete behavioural and network data are available, analysis of network-behaviour relations could be used to parametrise more flexible simulations within the Stochastic Actor-Oriented Modelling framework (McMillan & Schaefer, 2021). For example, this approach can be used to model different intervention impacts on targets (e.g. how does the intervention influence

target behaviour in relation to other factors?). It can also model behaviour as a dynamic continuous outcome, whereas our model only allows for adoption (not discontinuance), and include other important predictors of behaviour such as individual attributes, all of which can be parameterized using empirical data (Steglich, Snijders & Pearson, 2010). Beyond modelling the diffusion of behaviour, relative cost-effectiveness analyses can also differ between cases, depending on costs of intervention, data collection, and the aims of the intervention.

Network theory more generally suggests universal improvements to intervention design which are supported by our results. In particular we show that selecting targets in clusters is more likely to result in diffusion of complex behaviours than targeting individuals from across a network (Centola, 2018; Beaman *et al.*, 2014). Conservationists could easily apply this insight. For example, rather than invite conservation leaders from across the community, we could select one using a rule-of-thumb (such as the village chief) and ask them to invite their close connections to participate in the intervention. In Cambodia, anecdotal evidence suggests that after switching from village-wide meetings to small meetings with groups of related farmers, a 50% increase in recruitment to a conservation agriculture scheme was achieved in one village (de Lange, Milner-Gulland & Keane, 2019).

Our study shows that network analysis has the potential to improve conservation interventions on three levels. First, collection of sociometric data can identify optimal sets of targets for diffusing complex behaviours that outperform other strategies. However, this is unlikely to be cost-effective for small or low-cost interventions where resources are better spent targeting more individuals, selected via cheaper means. Second, sociometric data can be used in combination with other knowledge to produce context-specific generalised rules-of-thumb for targeting interventions in some cases. This approach may be valuable for refining large-scale interventions; in our case, this approach is cost-effective if a large number of villages are included in the intervention (although the absolute cost of data collection is still low). Simple value of information analyses combined with

simulations can help to guide these decisions (Rhodes *et al.*, 2020; Akbarpour, Malladi & Saberi, 2020; Canessa *et al.*, 2015). Third, the large literature on network interventions (Valente, 2012) suggests improvements to intervention design that apply across contexts, such as the use of clustered targeting strategies (Centola, 2018). Given the relative cost of collecting sociometric data, this is likely to be the most generally useful contribution of network science to conservation practice. Conservationists should continue to incorporate these insights into their interventions (Groce *et al.*, 2018), while further research on social networks within different conservation contexts is needed to identify further applicable insights.

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Ethics

This research was approved by the ethics committee of the School of Geosciences, University of Edinburgh (No. 132 & 191, 2017, 2018). Informed consent was provided by all respondents individually and by the village chiefs. Permission for the research was granted by the Ministry of Environment of the Royal Government of Cambodia, and the Provincial Governor's office of Preah Vihear. We have no conflicts of interest to declare.

393 [Data availability statement](#)

394 *The datasets and code supporting this article are available at:*

395 *<https://github.com/emieldelange/Network-Simulations>*

396 [Authors contributions](#)

397 *Conceptualisation: EdL, EJMG, AK. Methodology: EdL, EJMG, AMD, AK. Formal analysis, data*

398 *collection, & writing (original draft): EdL. Writing (review & editing): all co-authors. Supervision:*

399 *EJMG & AK. Funding acquisition: EdL & AK.*

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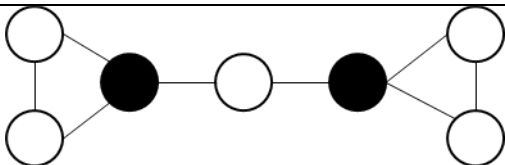
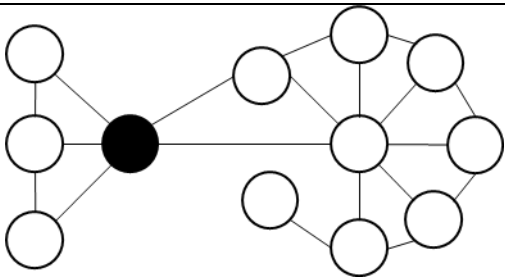
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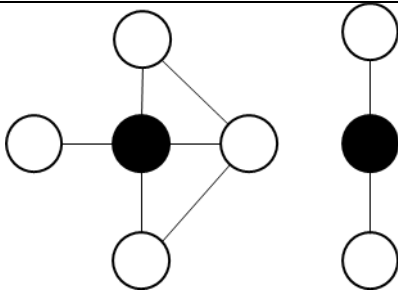
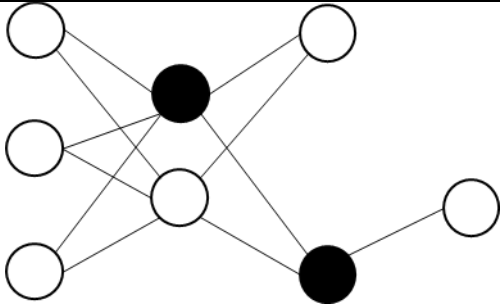
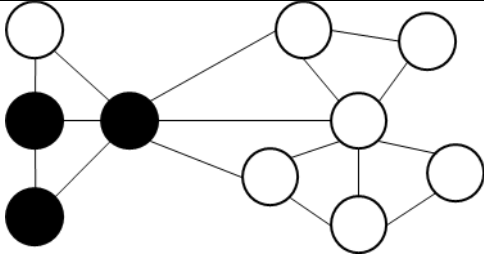
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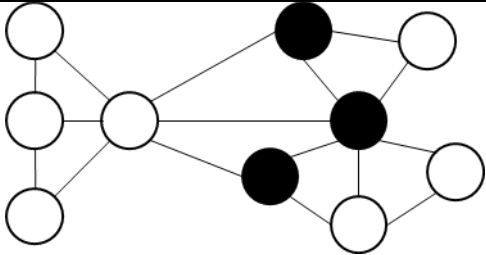
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556

557 Table 1: Targeting strategies informed by the network interventions literature. The first four are
 558 "key-players" approaches selecting individuals that span the networks, while the last two are
 559 clustering strategies selecting groups of connected individuals. Diagrams for key-players approaches
 560 (1 to 4) are adapted from Mbaru & Barnes (2017)).

Targeting strategy	Case study rationale	Modelling strategy	Example	Diagram
In-degree centrality	Identifies popular individuals who have many connections with others and are influential.	We select the individuals with the highest in-degree centrality, using the Key-players Algorithm	(Mbaru & Barnes, 2017)	
Betweenness centrality	Identifies individuals who can broker information between disconnected groups	We select the individuals with the highest betweenness centrality, using the Key-players	(Mbaru & Barnes, 2017)	

		Algorithm		
Closeness centrality	Identifies individuals who can rapidly spread information	We select the individuals with the highest closeness centrality, using the Key-players Algorithm	(Mbaru & Barnes, 2017)	
Eigenvector centrality	Identifies individuals with influential friends, who can facilitate the spread of the hotline	We select the individuals with the highest eigenvector centrality, using the Key-players Algorithm	(Mbaru & Barnes, 2017)	
Clusters	Use of the hotline is socially sensitive so	We select random individuals and then	(Beaman <i>et al.</i> , 2014)	

	targeting groups of friends is more likely to result in adoption.	include all their nominated peers.		
Combined approach	Groups of friends that are well-connected are more likely to adopt, and more likely to spread the hotline to others.	We select individuals with high centrality and include their connected peers.	-	

561

562

563 Table 2: Targeting strategies used in our simulated intervention, informed by a review of the
 564 conservation science literature.

Targeting strategy	Case study rationale	Modelling strategy	Example
Negative attitudes to the behaviour	Changing the behaviour of those individuals least likely to support reporting of poisoning will be most effective	We select the individuals least likely to want to report poisoning from our sample	(Saypanya <i>et al.</i> , 2013; Jones <i>et al.</i> , 2019; Kamins <i>et al.</i> , 2015)
Positive attitudes to the behaviour	Targeting individuals already predisposed to using the hotline will be most effective.	We select the individuals most in favour of reporting poisoning from our sample	(Jones <i>et al.</i> , 2019; Metcalf <i>et al.</i> , 2018)
Wealth	Wealthy individuals are thought to be influential, and they will help to promote use of the hotline.	We select the heads of the wealthiest households	(Olmedo, Sharif & Milner-Gulland, 2017; Mbaru & Barnes, 2017)
Leadership	Local leaders are trusted, have good local knowledge, and will provide legitimacy to the hotline.	We select individuals occupying formal leadership positions in the community, such as the village chief and sub-chief, leaders & secretaries in the community forest committee.	(Saypanya <i>et al.</i> , 2013; Gibson & Marks, 1995; Mbaru & Barnes, 2017; Day <i>et al.</i> , 2014; Steinmetz <i>et al.</i> , 2014)
Gatekeeper	We have an existing relationship with the village chief. We can rely on his local knowledge and assume he has influential	We select individuals within our network connected to the village chief through any kind of tie.	(Gibson & Marks, 1995)

	friends.		
Convenience	Hosting an event at the village hall is likely to attract an interested crowd and is convenient.	We select a random set of individuals, with a bias towards women and those living near the village hall, as we know these are more likely to attend.	(Cartwright, Wall & Placide Kaya, 2012; Saypanya <i>et al.</i> , 2013)
Conservationists	We have existing relationships with some individuals and know they are committed to conservation. We can rely on their local knowledge.	We select individuals known to be engaged in conservation activities in general, such as members of the community forest and Ibis Rice committees.	(Day <i>et al.</i> , 2014)
School students	School children are more easily influenced and may influence their parents.	Not considered in this study	(Damerell, Howe & Milner-Gulland, 2013; Freund <i>et al.</i> , 2020; Steinmetz <i>et al.</i> , 2014; Padua, 1994)
Random	Without specific information upon which to base our targeting we choose random residents in the village.	We select a random set of individuals.	(Jones <i>et al.</i> , 2019; Day <i>et al.</i> , 2014; Baruch-Mordo <i>et al.</i> , 2011; Saypanya <i>et al.</i> , 2013)

565

566

567 Table 3: Costs required to achieve a target AUC for four example strategies (one from each type), at
568 a low communication probability. The costs are calculated based on interpolated effort levels.
569 Missing costs indicate that it was not possible to achieve this target AUC using this particular
570 strategy in our simulations. For explanations of the strategies, see Table 2.

Strategy	Target AUC for complex contagion			Target AUC for simple contagion		
	10%	15%	20%	60%	70%	80%
KP In-degree	\$5349	\$5475	\$5488	-	\$5269	\$5330
Gatekeeper	\$301	\$353	-	\$91	\$153	\$513
Wealth	\$2555	\$2682	-	\$2340	\$2402	\$2712
Random	\$379	-	-	\$131	\$178	\$510

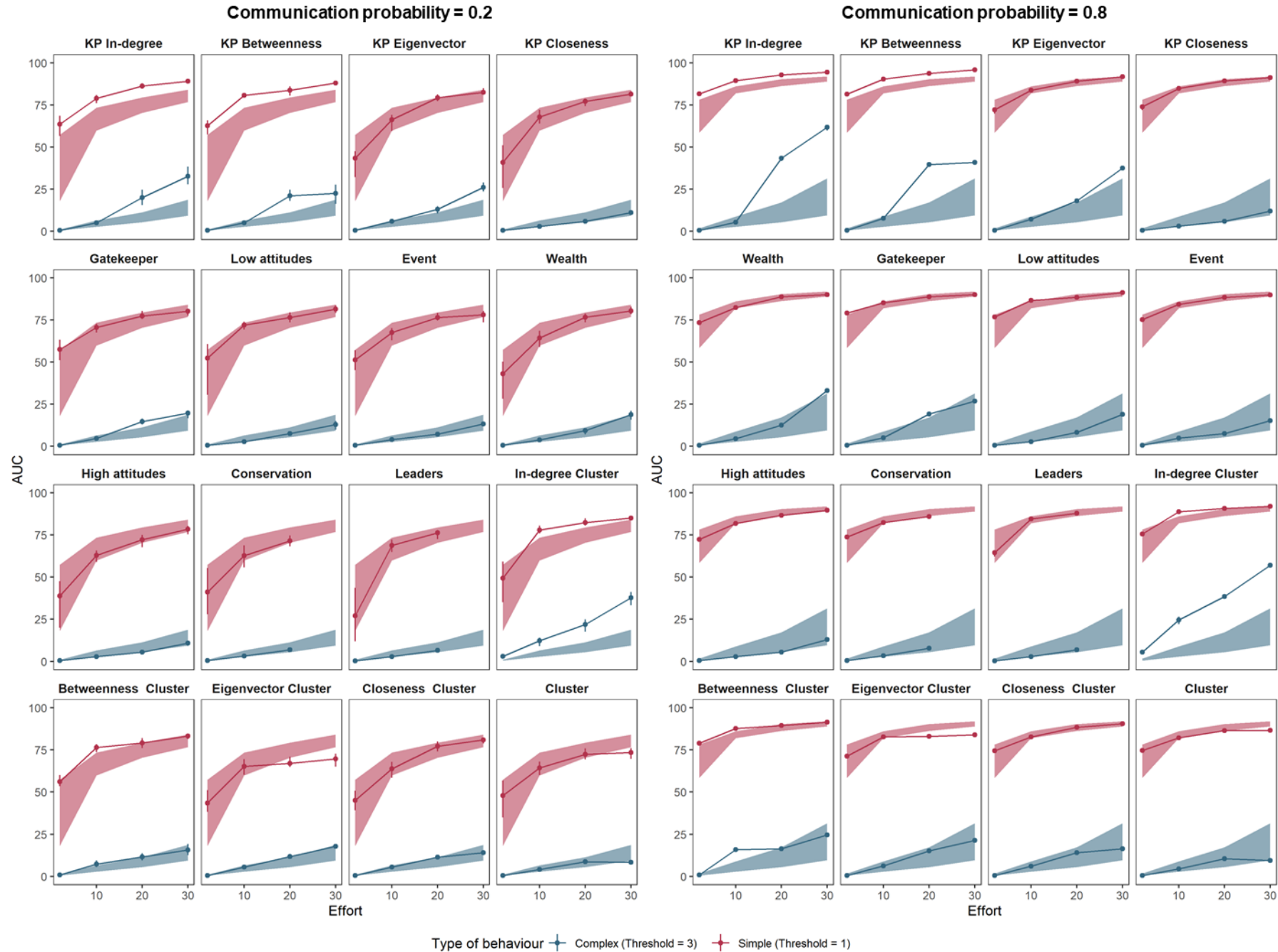


Figure 1: Performance of different targeting strategies at diffusing an innovation, based on simulations using the measured social network. Each strategy is simulated at four levels of effort (2, 10, 20, & 30 targeted individuals) except for 'conservation' and 'leaders' which are not simulated at $n=30$, because not enough of these people existed within the network. Performance is measured as the area under the diffusion curve (AUC) as percentage of the maximum possible diffusion at time $t=20$. Bootstrapped 95% confidence intervals are shown. The shaded area is the 95% confidence interval range for simulations on 30 randomly generated sets of targets, acting as a null comparator. If the line falls within the shaded area, its performance is within the bounds of random targeting. Colours indicate the threshold of diffusion: blue for complex contagions such as conservation behaviours, and red for simple contagions such as information. On the left are results when the communication probability (i.e., the probability of communication between two connected individuals) is low (0.2), and on the right it is high (0.8). See Table 2 for explanations of the strategies.

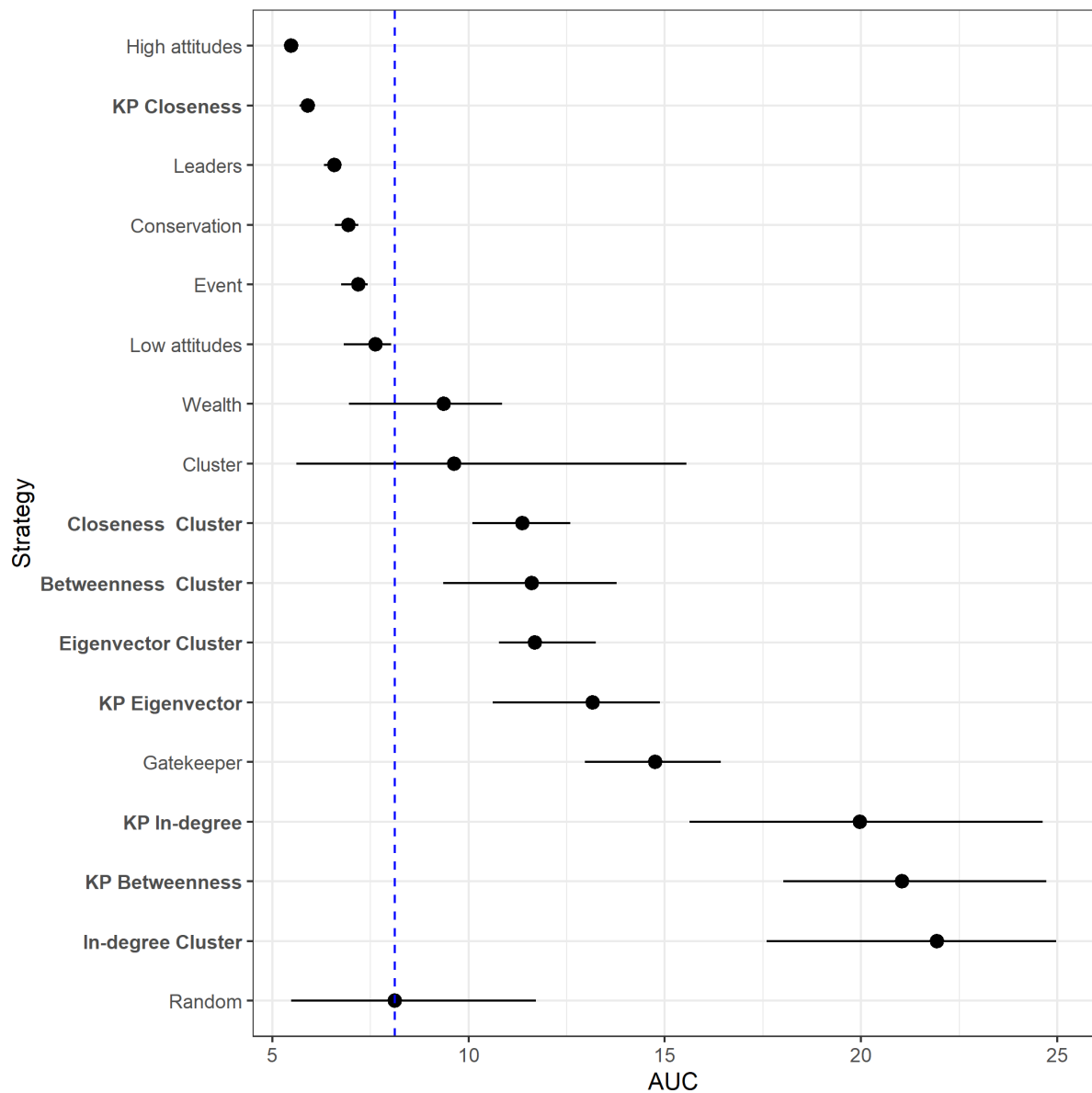


Figure 2: Strategy performance ordered by mean AUC. When targeting 20 individuals, only sociometric strategies (in bold) and targeting through the gatekeeper perform better than random at diffusing a complex contagion at low listening probability. The AUC represents the percentage of the maximum possible diffusion achieved within 20 time periods. Bootstrapped 95% confidence intervals are shown from 20 model runs. For Random, confidence intervals are bootstrapped for 20 runs across 30 randomly generated sets, and the median set is shown by the dotted line. See Table 2 for explanations of the strategies.

Supplementary materials

1. Qualitative identification of relevant ties.

We conducted qualitative research to understand social interactions within our study area and to identify relevant ties to measure. We visited twelve villages (including the focal village) from June to September 2017, (de Lange *et al.*, 2020) (de Lange *et al.*, 2020) (de Lange *et al.*, 2020) conducted two focus group discussions in each village (one for each gender), and interviewed informants such as those in official positions, shopkeepers, and others (see de Lange *et al.* 2020 in Oryx for further information about this study). In these discussions we asked participants where they received information about related topics such as agriculture, conservation, health, and hunting. We asked them to reflect on what makes certain information sources trustworthy and about influential relationships, such as individuals trusted to resolve conflicts, agricultural, or health issues. Additionally, we observed behaviour during our time in these villages, drew on our own experience working in rural Cambodia, consulted with local experts, and with the literature.

We then coded the data to identify discrete forms of interactions which could feasibly be measured and selected a set of ties to measure in consultation with local experts and NGO staff.

2. Description of ties included in the network

Household visits

Throughout the year, adult residents in Preah Vihear province spend much of the day working at their farms or gathering food in the forest. These activities are usually done in small groups from the same household, and because the farms are located far from the village, there is little opportunity for social contact with others, unless two farms happen to be located close to one another, which is rarely the case. At some parts of the year, farmers will stay in small huts at their farms for extended periods, further limiting opportunities for social contact. At other parts of the year, such as when the rains first start or when harvests are complete, all farmers will stay in the village to participate in social and religious festivals. However, for most of the year, adults will return home to the village each evening and return to the farm in the early morning. The evening is therefore an opportunity to relax, eat, and socialise. Residents will visit others at their homes to check in, catch up on gossip, and hang out. This applies to both men and women, although women are more likely to stay home during the day if they have young children and may visit with relatives and neighbours throughout the day. We asked respondents to name those who they visited at their homes during their free time. This is a directional tie, meaning the respondent visiting a nominated other does not necessarily mean the other also visits the respondent.

Household co-residence

The household is the core unit of social organisation in Khmer society. Multiple generations of adults may live in the same household as it is customary for the youngest daughter to remain at home and to care for the parents. When the youngest daughter marries, her husband will also join the household, and together they will eventually take over the running of the household and inherit the house. As members of the same household eat together every day, and work together on the farm,

much communication occurs between them. We generated a census of each household in the village and generated co-residence ties between all members of the same household.

3. Details of cleaning and verification procedures for network data

Firstly, the research team manually corroborated and corrected respondent names against a village census provided by the village chief. Secondly, we used fuzzy matching in R to identify all names in the data that differed from other names by less than three characters. Third, we generated a list of names that occurred only once in our dataset. Having compiled a set of potentially problematic cases using these two methods, we manually checked each name to see if there were obvious identity confusions, or if nicknames were used. We used kinship data we had collected to create a genealogy, which served as a reference to check and correct possible misspellings. For example, if Rob Franks had nominated Tim Franks and Mary Franks as siblings, but Mary had nominated Rob and Tom as siblings, we presumed Tim and Tom were alternate spellings of the same person. We selected one option and corrected any occurrences of this name in the dataset. This is a conservative strategy given that illiteracy is prevalent, and many possible spellings exist for any name in Khmer.

4. Likert items for measuring attitudes towards reporting poisoning

If I see poisoning and report it, the village will be safer

តើអ្នកយល់ស្របដែរឬទេថា,ប្រសិនបើអ្នកឃើញមានការបំពុលហើយរាយការណ៍ តើអ្នកភូមិនឹងមានសុវត្ថិភាព
ជាងមុនដែរឬទេ?

Strongly disagree 1 – 2 – 3 – 4 – 5 Strongly Agree – Don't know

If you see poisoning, it is good to keep it to yourself and not report it

តើអ្នកយល់ស្របដែរឬទេថា,ប្រសិនបើអ្នកឃើញមានការបំពុល វាជាឿងល្អដែលអ្នកគួរលាក់ទុកហើយមិនធ្វើ
ការរាយការណ៍ទៅអាជ្ញាធរ ?

Strongly disagree 1 – 2 – 3 – 4 – 5 Strongly Agree – Don't know

Reporting poisoning is a good way to keep livestock safe

តើអ្នកយល់ស្របដែរឬទេថា,ការរាយការណ៍ពីការបំពុលជាវិធីសាស្ត្រដ៏ល្អមួយដើម្បីបាននូវសុវត្ថិភាពជីវិតសត្វ?

Strongly disagree 1 – 2 – 3 – 4 – 5 Strongly Agree – Don't know

If I see poisoning and report it, no one will come to clean the environment

តើអ្នកយល់ស្របដែរឬទេថា,ប្រសិនបើអ្នកឃើញការបំពុលហើយរាយការណ៍ គ្មាននរណាម្នាក់នឹងមកសម្អាតបរិស្ថានរបស់អ្នកទេ ?

Strongly disagree 1 – 2 – 3 – 4 – 5 Strongly Agree – Don't know

5. Literature search

To identify targeting strategies used in conservation behaviour change interventions we conducted a brief literature search. We searched the Web of Science database using the keywords: “intervention AND behavi*”, filtered by the “biodiversity conservation” category. We scanned over 200 resulting abstracts and selected papers describing real behaviour-change interventions. We searched these for information about targeting strategies and identified 15 papers with clear descriptions. We also drew on the papers cited in the following reviews: (Nilsson et al., 2016; Olmedo, Sharif & Milner-Gulland, 2017; Ryan et al., 2020). We also drew on our experiences collaborating with conservation practitioners.

Nilsson, D., Baxter, G., Butler, J.R.A. & Mcalpine, C.A. (2016) How do community-based conservation programs in developing countries change human behaviour? A realist synthesis. *BIOC*. [Online] 200, 93–103. Available from: doi:10.1016/j.biocon.2016.05.020.

Olmedo, A., Sharif, V. & Milner-Gulland, E.J. (2017) Evaluating the Design of Behaviour Change Interventions: A Case Study of Rhino Horn in Vietnam. *Conservation Letters*. [Online] Available from: doi:10.1111/conl.12365.

Ryan, J., Mellish, S., Dorrian, J., Winefield, T., et al. (2020) Effectiveness of biodiversity-conservation marketing. *Conservation Biology*. [Online] 34 (2), 354–367. Available from: doi:doi:10.1111/cobi.13386.

6. Centrality measures used

In-degree centrality

In-degree centrality is the number of incoming connections each individual has. For example, in the household visits network, this is the number of times an individual is nominated by others. Individuals with high in-degree centrality are therefore directly connected to many other individuals. They are able to rapidly diffuse contagions.

Betweenness centrality

Betweenness centrality is the number of times an individual falls on the shortest possible path between each other pair of individuals. It is a measure of the power an individual has to broker the exchange of information between others.

Closeness centrality

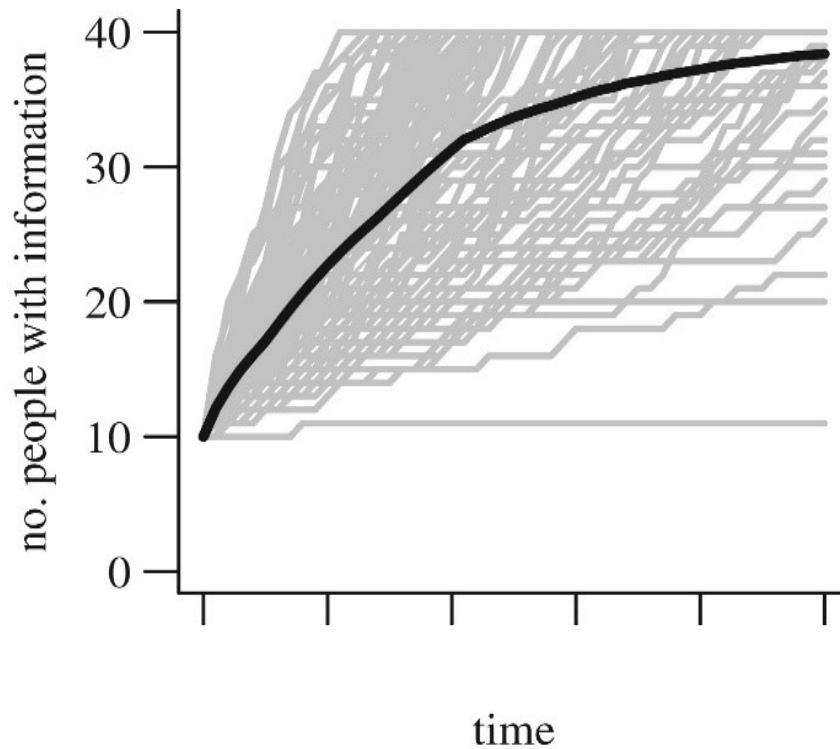
Closeness centrality is sum of the shortest distance from an individual to every other individual in the network. In other words, an individual with high closeness centrality has relatively few degrees of separation to all other individuals in the network and can therefore reach any other person relatively easily. They are able to spread information, or simple contagions, rapidly.

Eigenvector centrality

Eigenvector centrality is the extent to which an individual is connected to other individuals with high eigenvector centrality. It is a recursive measure, which indicates an individual’s ability to influence or inform other influential individuals.

5. Area under the diffusion curve (AUC)

At each time period more individuals in the network adopt the contagion. This can be visualised as a cumulative diffusion curve (adapted from Dobson et. al., 2019):



The area under this curve therefore gives an indication of both the scale and the rate of adoption.

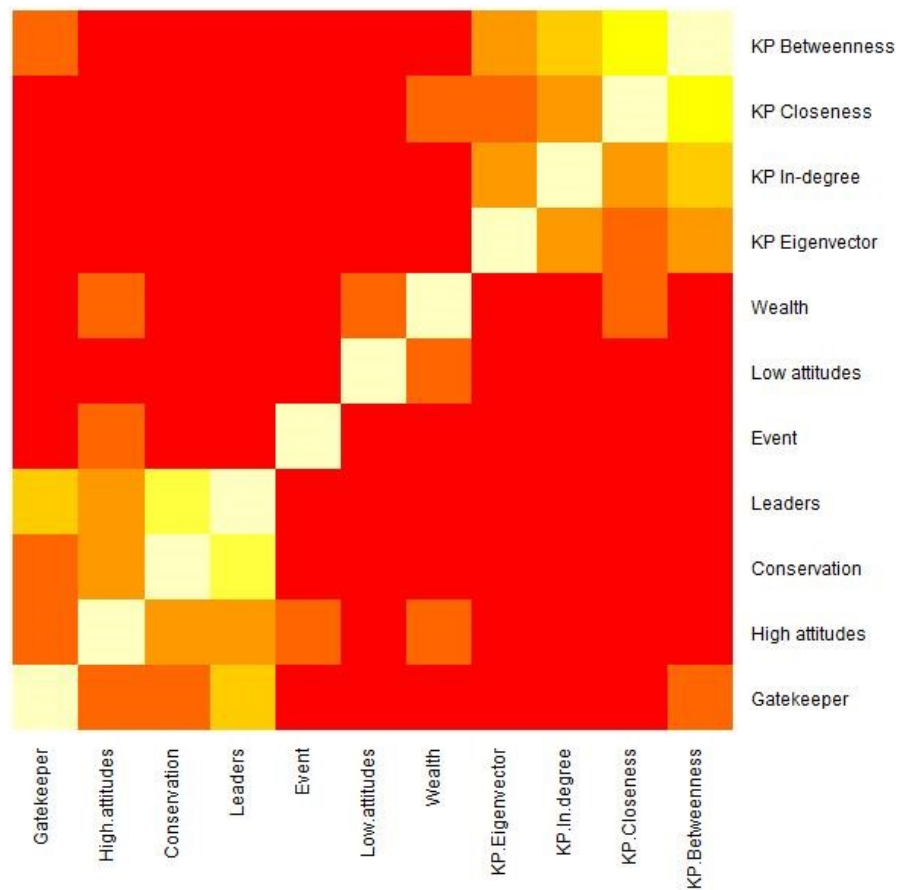
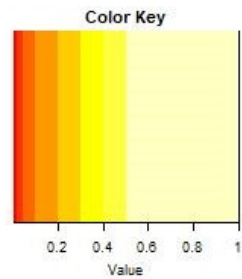
Supplementary Table 1: Descriptive statistics from the sample

Variable	Definition	Value
Gender	Male	159 (44%)
	Female	206 (56%)
Age	Mean age in years	34 (SD = ± 14)
Married	Yes	326 (89%)
	No	38 (11%)
Household size	Mean number of adults surveyed per household	2.4 (SD = ± 1.0)
Network statistics	Percentage of respondents nominating others in the household visit network	92%
	Mean out-degree (i.e. number of nominations) in the household visit network	1.92 (SD = ± 1.14)
	Mean in-degree (i.e. number of times nominated by others) in the household visit network	3.84 (SD = ± 2.54)
	Mean in-degree in the combined household visit and co-residence network	7.40 (SD = ± 3.16)
	Density (i.e. the proportion of all possible ties that are observed) of the combined network.	0.01

	Number of components (i.e. disconnected parts) in the combined network	4
	Diameter (i.e. largest number of steps between any two individuals) of the largest component in the combined network	18 ties
	Transitivity (i.e. density of closed triangles) of the combined network	0.31
Attitude	Mean attitude towards reporting poisoning, where 20 is the most positive, and 4 is the most negative.	15.1 (SD = \pm 2.22)

Supplementary table 2: Jaccard similarity index calculated for all sets of targets (n = 10)

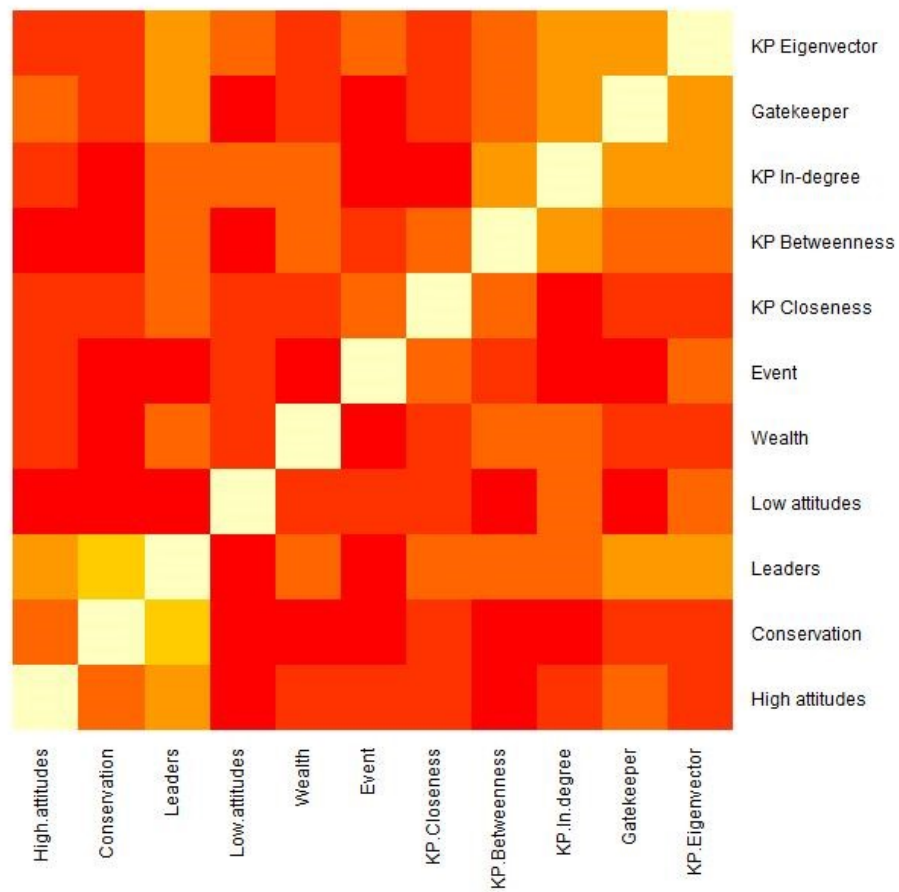
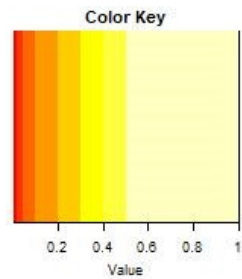
	KP In-degree	KP Betweenness	KP Closeness	KP Eigenvector	Low attitudes	High attitudes	Wealth	Leaders	Gatekeeper	Event	Conservation
KP In-degree	1.000	0.250	0.111	0.176	0.000	0.000	0.000	0.000	0.000	0.000	0.000
KP Betweenness	0.250	1.000	0.333	0.111	0.000	0.000	0.000	0.000	0.053	0.000	0.000
KP Closeness	0.111	0.333	1.000	0.053	0.000	0.000	0.053	0.000	0.000	0.000	0.000
KP Eigenvector	0.176	0.111	0.053	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Low attitudes	0.000	0.000	0.000	0.000	1.000	0.000	0.053	0.000	0.000	0.000	0.000
High attitudes	0.000	0.000	0.000	0.000	0.000	1.000	0.053	0.111	0.053	0.053	0.111
Wealth	0.000	0.000	0.053	0.000	0.053	0.053	1.000	0.000	0.000	0.000	0.000
Leaders	0.000	0.000	0.000	0.000	0.000	0.111	0.000	1.000	0.250	0.000	0.429
Gatekeeper	0.000	0.053	0.000	0.000	0.000	0.053	0.000	0.250	1.000	0.000	0.053
Event	0.000	0.000	0.000	0.000	0.000	0.053	0.000	0.000	0.000	1.000	0.000
Conservation	0.000	0.000	0.000	0.000	0.000	0.111	0.000	0.429	0.053	0.000	1.000



SM Figure 1: A heatmap showing the Jaccard similarity between each pair of target sets at size $n=10$. A lighter colour indicates greater similarity.

Supplementary table 3: Jaccard similarity index calculated for all sets of targets (n = 20)

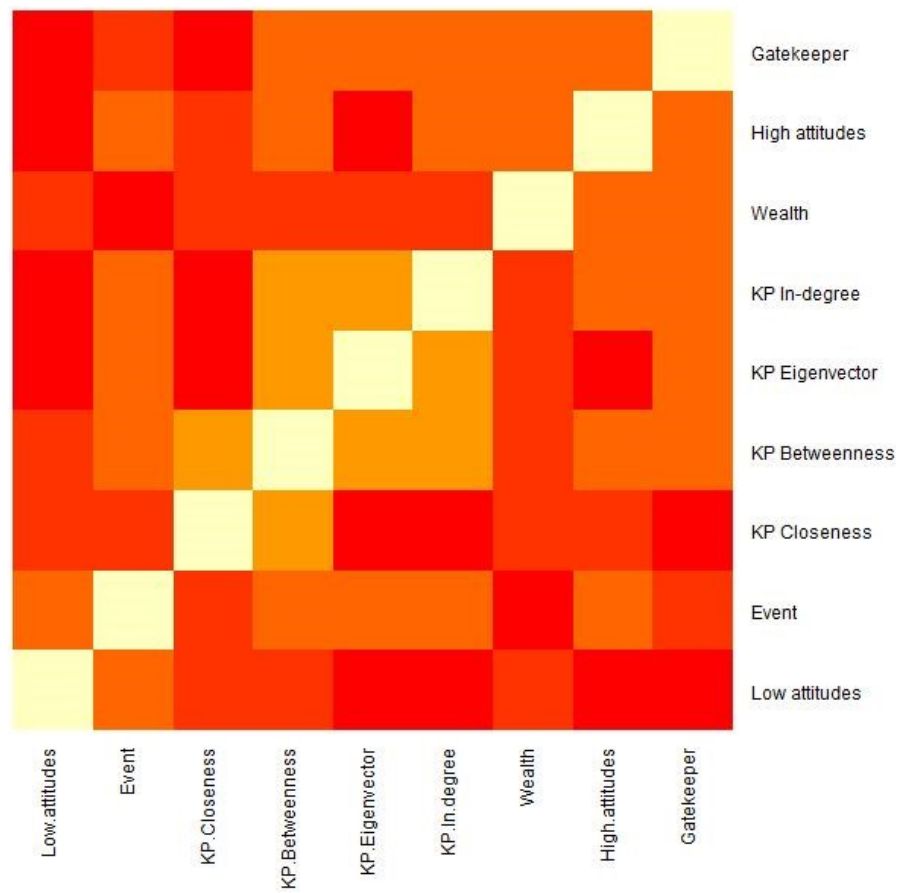
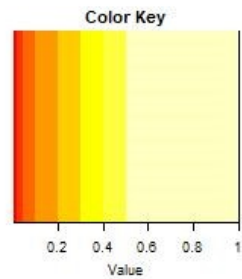
	KP In-degree	KP Betweenness	KP Closeness	KP Eigenvector	Low attitudes	High attitudes	Wealth	Leaders	Gatekeeper	Event	Conservation
KP In-degree	1.000	0.143	0.000	0.143	0.053	0.026	0.053	0.053	0.111	0.000	0.000
KP Betweenness	0.143	1.000	0.053	0.081	0.000	0.000	0.053	0.053	0.053	0.026	0.000
KP Closeness	0.000	0.053	1.000	0.026	0.026	0.026	0.026	0.053	0.026	0.081	0.026
KP Eigenvector	0.143	0.081	0.026	1.000	0.053	0.026	0.026	0.143	0.111	0.081	0.026
Low attitudes	0.053	0.000	0.026	0.053	1.000	0.000	0.026	0.000	0.000	0.026	0.000
High attitudes	0.026	0.000	0.026	0.026	0.000	1.000	0.026	0.111	0.053	0.026	0.083
Wealth	0.053	0.053	0.026	0.026	0.026	0.026	1.000	0.053	0.026	0.000	0.000
Leaders	0.053	0.053	0.053	0.143	0.000	0.111	0.053	1.000	0.111	0.000	0.219
Gatekeeper	0.111	0.053	0.026	0.111	0.000	0.053	0.026	0.111	1.000	0.000	0.026
Event	0.000	0.026	0.081	0.081	0.026	0.026	0.000	0.000	0.000	1.000	0.000
Conservation	0.000	0.000	0.026	0.026	0.000	0.083	0.000	0.219	0.026	0.000	1.000



SM Figure 2: A heatmap showing the Jaccard similarity between each pair of target sets at size $n=20$. A lighter colour indicates greater similarity.

Supplementary table 4: Jaccard similarity index calculated for all sets of targets (n = 30)

	KP In-degree	KP Betweenness	KP Closeness	KP Eigenvector	Low attitudes	High attitudes	Wealth	Gatekeeper	Convenience
KP In-degree	1.000	0.176	0.000	0.200	0.017	0.053	0.034	0.000	0.094
KP Betweenness	0.176	1.000	0.132	0.111	0.034	0.053	0.034	0.000	0.055
KP Closeness	0.000	0.132	1.000	0.000	0.034	0.034	0.034	0.000	0.018
KP Eigenvector	0.200	0.111	0.000	1.000	0.017	0.017	0.034	0.000	0.074
Low attitudes	0.017	0.034	0.034	0.017	1.000	0.000	0.034	0.000	0.000
High attitudes	0.053	0.053	0.034	0.017	0.000	1.000	0.053	0.000	0.074
Wealth	0.034	0.034	0.034	0.034	0.034	0.053	1.000	0.000	0.074
Gatekeeper	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000
Convenience	0.094	0.055	0.018	0.074	0.000	0.074	0.074	0.000	1.000



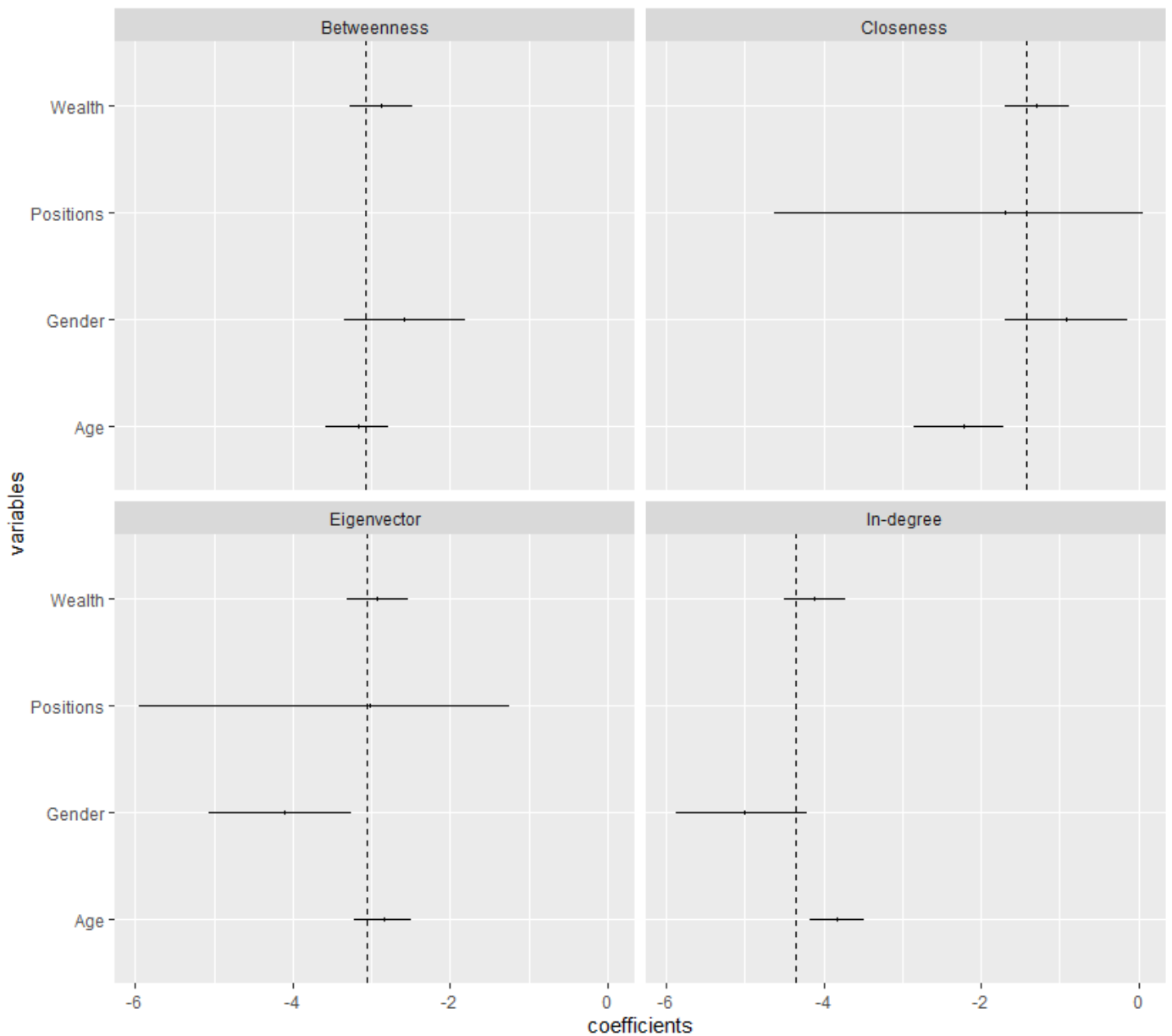
SM Figure 3: A heatmap showing the Jaccard similarity between each pair of target sets at size $n=30$. A lighter colour indicates greater similarity.

1 Supplementary table 5: Results of logistic regressions

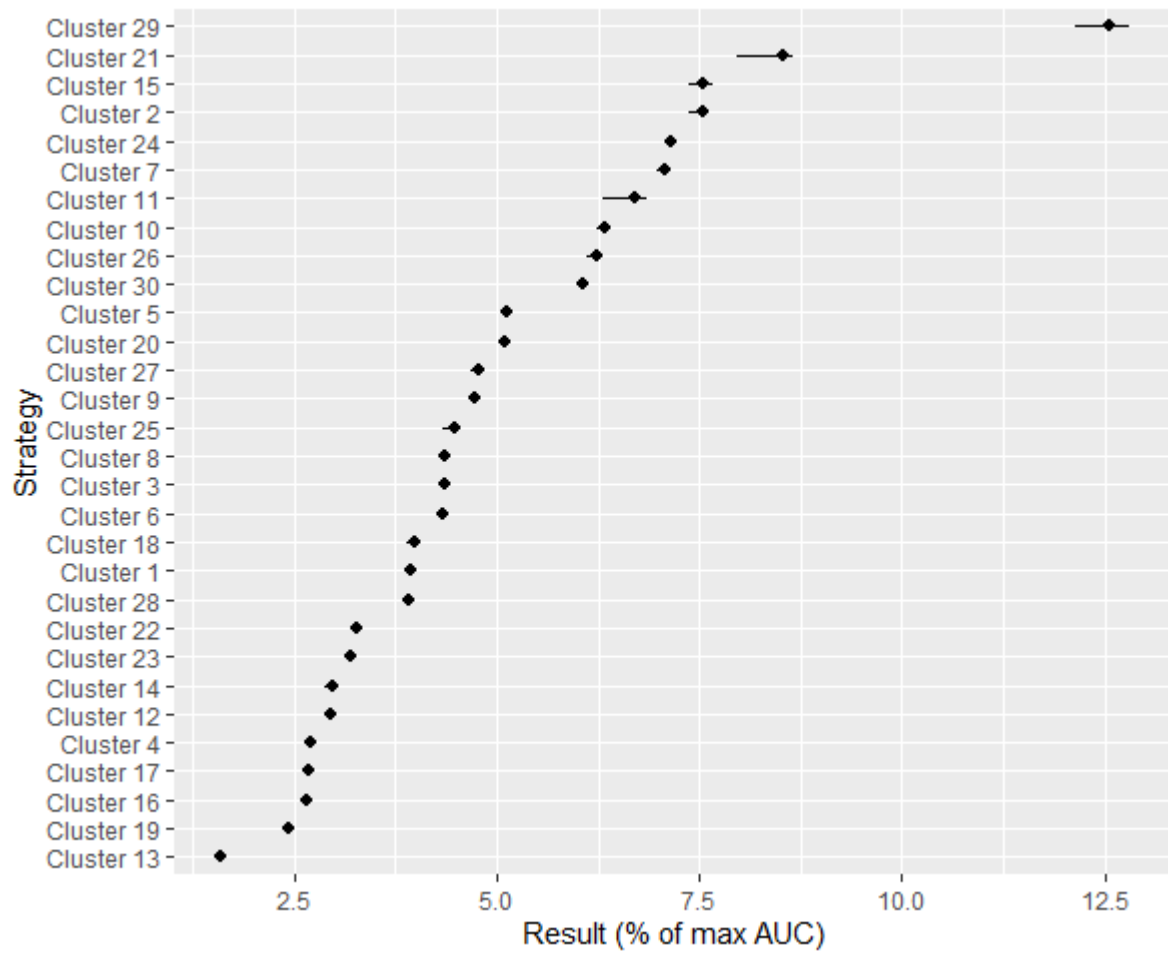
2

Dependent variable: Predictor variable:	In-degree centrality key-player			Betweenness centrality key- player			Closeness centrality key-player			Eigenvector centrality key-player		
	Estimate	S.E.	P-value	Estimate	S.E.	P-value	Estimate	S.E.	P-value	Estimate	S.E.	P-value
Intercept	-4.352	0.949	<0.001	-3.068	0.949	0.001	-1.418	0.965	0.142	-3.052	0.895	0.001
Age	0.516	0.174	0.003	-0.097	0.201	0.629	-0.803	0.287	0.005	0.208	0.183	0.254
Gender (male)	-0.652	0.421	0.121	0.487	0.385	0.206	0.494	0.393	0.209	-1.045	0.453	0.021
Wealth	0.234	0.198	0.237	0.185	0.204	0.364	0.127	0.204	0.533	0.127	0.194	0.513
Leadership positions	-15.189	983.031	0.988	-15.426	1014.778	0.988	-0.268	1.079	0.804	0.041	1.086	0.970

3



SM Figure 4: Results from logistic binary regressions testing (see supplementary table 5) for associations between some key individual attributes (wealth, formal leadership positions, gender, and normalised age) with inclusion in each of four key-players sets, size 30, calculated using the centrality measures: In-degree, Betweenness, Closeness, and Eigenvector. The effect sizes are shown bounded by the 95% confidence intervals. The intercept is shown as a dotted line. Formal leadership positions is omitted from the plot for In-degree and Betweenness centrality, as the confidence intervals exceeded the range of the graph.



SM Figure 5: The result (as a percentage of the maximum AUC) of diffusion simulations for a complex contagion using 30 randomly generated sets of clusters (size = 10), communication probability = 0.2. Bootstrapped 95% confidence intervals are shown.

Supplementary table 5: A rough budget for each level of intervention effort. An intervention targeting two people could consist of a meeting with two NGO staff at the target's homes with provision of personal materials. An intervention with thirty targets requires coordination with the village chief to invite participants, provision of food and refreshments, and production of public materials to be displayed. At least five NGO staff will be required.

Item	Two targets	Ten targets	Twenty targets	Thirty targets
Staff costs	22	36	48	72
Material costs	20	90	200	280
Event costs	10	20	100	150
Total (USD)	\$52	\$146	\$348	\$502

Supplementary table 6: a rough budget for a research team of two junior Cambodian researchers to undertake six weeks of work collecting network data, or four weeks of work for other data, in our focal village. This includes time for preparation, training, and some preparatory qualitative work. For network data, this also include a consultancy fee for a network analyst to clean the data and identify the target sets. Conventional strategies requiring other data are 'wealth', 'relatively negative attitudes', and 'relatively positive attitudes'. Other conventional strategies did not require additional data collection and can be implemented using local knowledge

Item	Network data (USD)	Other data (USD)
Research staff costs	1200	800
Food & accommodation	1260	840
Equipment	200	200
Transport & fuel	200	160
Respondent gifts	200	200
Network analyst consultant	2000	-
Total	\$5160	\$2200