CONTRIBUTED PAPER

Conservation Biology

Effects of social networks on interventions to change conservation behavior

Emiel de Lange[1,2] 🄳 | **E.J. Milner-Gulland**[2] 🄳 | **Aidan Keane**[1] 🄳

[1] School of Geosciences, University of Edinburgh, Edinburgh, UK

[2] ICCS, Department of Zoology, University of Oxford, Oxford, UK

Correspondence
Emiel de Lange, School of Geosciences, University of Edinburgh, 1 Drummond Street, Edinburgh EH9 3JW, UK.
Email: emiel.r.delange@gmail.com

Article Impact statement: Understanding how social networks influence behavioral outcomes can enable interventions to harness social influences for conservation.

Abstract

Social networks are critical to the success of behavioral interventions in conservation because network processes such as information flows and social influence can enable behavior change to spread beyond a targeted group. We investigated these mechanisms in the context of a social marketing campaign to promote a wildlife poisoning hotline in Cambodia. With questionnaire surveys we measured a social network and knowledge and constructs from the theory of planned behavior at 3 points over 6 months. The intervention initially targeted ∼11% (of 365) of the village, but after 6 months ∼40% of the population was knowledgeable about the campaign. The likelihood of being knowledgeable nearly doubled with each additional knowledgeable household member. In the short term, there was also a modest, but widespread improvement in proconservation behavioral intentions, but this did not persist after 6 months. Estimates from stochastic actor-oriented models suggested that the influences of social peers, rather than knowledge, were driving changes in intention and contributed to the failure to change behavioral intention in the long term, despite lasting changes in attitudes and perceived norms. Our results point to the importance of accounting for the interaction between networks and behavior when designing conservation interventions.

KEYWORDS
impact evaluation, information flow, poison, social influence, social marketing, social norms, stochastic actor-oriented model, theory of planned behaviour

Efectos de las Redes Sociales sobre las Intervenciones para Alterar el Comportamiento de Conservación

Resumen: Las redes sociales son de mucha importancia para el éxito de las intervenciones conductuales en la conservación porque los procesos de las redes, como los flujos de información y la influencia social, pueden facilitar que los cambios conductuales lleguen más allá del grupo al que se desea modificar su comportamiento. Investigamos estos mecanismos dentro del contexto de una campaña de mercadotecnia social para promover una línea directa de atención al envenenamiento de fauna en Camboya. Mediante encuestas, medimos una red social y el conocimiento y las construcciones a partir de la teoría del comportamiento planeado en tres puntos a lo largo de seis meses. La intervención inicialmente se enfocó en ∼11% (de 365) de la aldea, pero después de seis meses ∼40% de la población tenía conocimiento sobre la campaña. La probabilidad de tener conocimiento sobre la campaña casi se duplicó con cada miembro adicional del hogar que adquiría dicho conocimiento. A corto plazo, también hubo una mejora modesta pero extensa de las intenciones conductuales en pro de la conservación, pero esto no continuó una vez

transcurridos los seis meses. Las estimaciones de los modelos estocásticos orientados hacia los actores sugirieron que la influencia de los pares sociales, y no el conocimiento, era la causante de los cambios en la intención y contribuyó al fracaso en la intención de cambio conductual a largo plazo, a pesar de los cambios duraderos en las actitudes y las normas percibidas. Nuestros resultados apuntan hacia la importancia de la consideración de las interacciones entre las redes sociales y el comportamiento cuando se diseñan las intervenciones de conservación.

Article Impact statement: Understanding how social networks influence behavioral outcomes can enable interventions to harness social influences for conservation.

【摘要】

社会网络对于保护中行为干预的成功与否至关重要, 因为信息流和社会影响等网络过程可以使行为改变扩散到目标群体之外。本研究利用柬埔寨一个推广野生动物中毒热线的社会营销活动, 对以上机制进行了调查。我们通过问卷调查, 在六个月内三个时间点测量了社会网络、知识和计划行为理论的概念。干预措施最初针对一个村子约 11% 的人口 (365人), 但在 6 个月后, 约 40% 的人口对该活动有所了解。我们发现, 受访者每增加一个了解情况的家庭成员, 其自身了解情况的可能性就增加一倍。在短期内, 愿意保护的行为意向有中度而普遍的提高, 但这在 6 个月后未能保持。随机行为者导向模型的估计表明, 与知识相比, 社会同伴的影响推动了意向的改变, 并导致长期行为意向改变的失败, 尽管受访者的态度和感知规范已发生持久的变化。我们的结果强调了设计保护干预措施时, 考虑社会网络和行为之间互作的重要性。【翻译: 胡怡思; 审校: 聂永刚】

INTRODUCTION

Biodiversity conservation practitioners and researchers are increasingly interested in designing interventions that influence human behavior (St. John et al., 2013). Social networks (i.e., the connections between individuals within a population) play a strong role in shaping behavior because individuals communicate with and influence one another (Borgatti et al., 2009; Prentice & Paluck, 2020). The structures of social networks therefore have important implications for environmental and conservation outcomes (Barnes et al., 2016; Bodin et al., 2006), and understanding how social networks influence behavior can enable practitioners to design more effective interventions (de Lange et al., 2019; Valente, 2012).

Human behavior is shaped by a wide range of beliefs and perceptions that individuals hold about the world. The theory of planned behavior, a widely used model for understanding intentional behaviors in individuals, posits that intentions to act in a particular way in a particular context are dependent on attitudes (i.e., whether the behavior is considered good or bad), perceptions of control (i.e., whether people believe they have the power to act), and perceived social norms (Ajzen, 1991). Perceived norms can be further described as descriptive (i.e., how others behave) or injunctive (i.e., expectations others have of behavior), which act independently (Schultz et al., 2016). These perceptions are updated as individuals receive information about the world around them (Schlüter et al., 2017).

An individual's social network can influence these constructs in important ways (Contractor & DeChurch, 2014; de Lange et al., 2019). As individuals communicate and share information about the world, this information alters beliefs and perceptions. For example, if a social peer provides useful information about using a new technology, this is likely to improve perceived ability to use the technology. If they share information about the benefits of a social program, attitudes toward participation may improve (Cai et al., 2015; Hilbert et al., 2017). The social contexts and relationships within which information is shared may influence how it is interpreted and acted on (Faraji-Rad et al., 2015; Pornpitakpan, 2004). These processes of information transfer and persuasion are at the heart of the classic diffusion of innovations theory, which describes how practices and technologies spread through social groups: initially, slowly, but they gain momentum as more individuals adopt the practice (Rogers, 2003). However, this theory has been criticized because it conceptualizes communication as a one-way process and focuses on the factors that enable diffusion rather than limiting factors (Karch et al., 2016).

Drawing on analysis and simulation of fine-scale network data, the more recently developed theory of "complex contagions" sheds light on why diffusion can fail and emphasizes
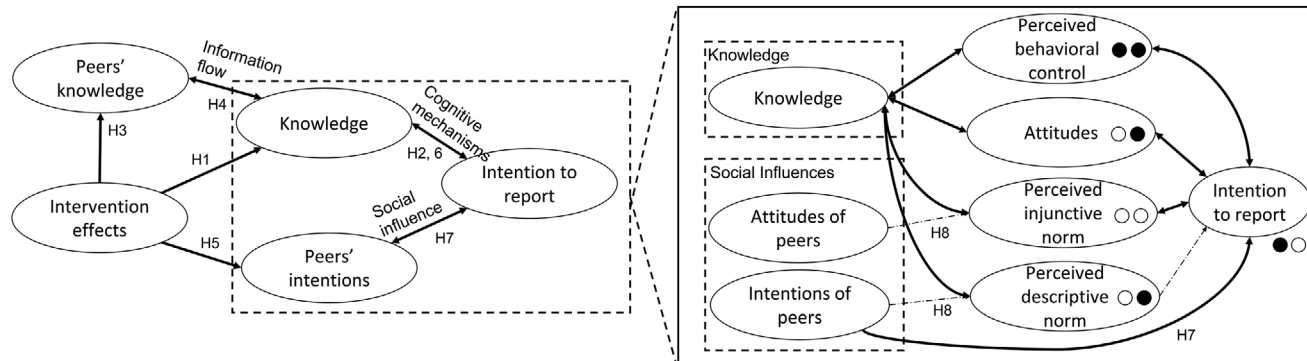
FIGURE 1 Relative to a campaign to promote a hotline for reporting wildlife poisoning in a Cambodian village, (left) the social processes, such as peer influence and exchange of information, and (right) the cognitive mechanisms through which individual intentions changed, based on the theory of planned behavior (dashed arrows, hypothesized relationships between variables not supported by the data; solid arrows, relations observed in the data; small black circles, changes in variable states 2 weeks [left] and 6 months [right] after the intervention; white circles, unchanged variables 2 weeks [left] and 6 months [right] after the intervention). The hypothesized mechanisms are intervention participants become more knowledgeable about reporting of poisoning (H1); intervention participants change their beliefs and intentions (H2); other villagers also become knowledgeable about the intervention (H3); other villagers gain knowledge about the intervention through their social networks (H4); other villagers also change their beliefs and intentions (H5); changes in intention throughout the village are due to increased knowledge (H6); changes in intention and beliefs throughout the village are due to peer influences (H7); and peer influences occur by changing perceived norms (H8).

the central role of social information (i.e., information about what others think and do) (Centola, 2010). This theory distinguishes between simple contagions such as information, which are transmitted in one direction through a single exposure, and complex contagions, which require social reinforcement or influence via multiple exposures in a social network to diffuse. Among other reasons, many behaviors are complex because there are social risks involved with adoption or because they require coordination between adopters (Centola, 2018). Information or perception about the behavior or attitudes of referent others in the individual's social networks are therefore critical and can influence behavior through changing perceived norms (Bicchieri, 2017; McDonald & Crandall, 2015). When norms and the behaviors of social referents are not supportive of a new practice, individuals may tend to comply or conform with the referents and diffusion will fail, even if they receive positive information about the practice and hold positive attitudes toward it (Cialdini & Goldstein, 2004). Conversely, positive social influences can drive widespread behavior change (Kim et al., 2015; Nakano et al., 2018).

Most network studies aiming to inform conservation practice use observations of social relations and behavior at a single point in time, usually before the intervention takes place (Groce et al., 2019). These data are used to predict how an intervention might harness social influence, such as by identifying influential individuals to target (Mbaru & Barnes, 2017) or delimiting relevant social groupings (Crona & Bodin, 2006). However, social change is a temporal process, and to untangle the mechanisms shaping behavior there is a need to move beyond cross-sectional approaches and adopt a longitudinal perspective (Robins, 2015; Shalizi & Thomas, 2011; Steglich et al., 2010). Such studies rarely have been conducted in conservation.

We aimed to understand how 2 important network processes—information flow and social influence—mediated the success or failure of a conservation intervention taking place in a part of Cambodia where purposeful pesticide misuse has been linked to the killing of threatened wildlife species and harm to humans. The intervention aimed to promote the use of a hotline for reporting pesticide contamination in one village (de Lange et al., 2020) and was designed to reach a small part of the population directly. We examined the village's social networks, then conducted a longitudinal analysis of behavior change by modeling survey data collected before and after the intervention.

We hypothesized that intervention participants gain knowledge about reporting (H1) that alters their beliefs and intention to report poisoning (H2), that nonparticipant residents become knowledgeable about the intervention (H3) because they receive information about the intervention through their social networks (H4), that nonparticipant residents change their beliefs and intentions to report poisoning (H6) because of increased knowledge (H6) and because they are influenced by the changing intentions of participants or others in their social networks (H7) (Figure 1), and that this social influence occurs through changing perceptions of social norms (H8). We used a combination of linear mixed-effect models (LMMs) and stochastic actor-oriented models (SAOMs) to test these hypotheses.

METHODS

Study context

Cambodia's Preah Vihear province contains the largest remaining lowland dry forests in Southeast Asia and is home to 28 critically endangered or endangered species (Clements et al., 2010). Many species rely on seasonal waterholes and are threatened by waterhole poisoning, first documented here in 2015. Poisoning is a method for harvesting wild meat practiced by some local farmers and youths. However, most residents do not approve

TABLE 1 An overview of data collection for a study of social network influences on outcomes of a conservation intervention in Cambodia that took place on February 13, 2019

Survey number	Dates	Before or after intervention	Data collected	No. of individuals (% completeness of network)	No. of Households (% completeness)
Preliminary	September 9 to July 10, 2017	Before	Social network	365 (100%)	100
1	January 21–27, 2019	Before	Psychological outcomes	181 (50%)	60
2	February 26 to March 6, 2019	After	Psychological outcomes and knowledge	283 (78%)	93
3	August 10–31, 2019	After	Psychological outcomes, knowledge, and social networks	191 (53%)	72

of this practice due to risks to human health and the environment, leading authorities in some villages to act against poisoning (de Lange et al., 2020). To support these efforts, the Wildlife Conservation Society (WCS) and the Department of Environment piloted the introduction of a reporting hotline, enabling anonymous reporting and fast response by authorities. A paired social marketing strategy aims to promote the hotline and influence perceptions and beliefs about reporting poisoning (Saypanya et al., 2013).

Study design

In one village in February 2019, WCS delivered an information session to 41 parents of children aged 10–15, a group identified as a priority audience (de Lange et al., 2020). The intervention aimed to improve attendees' intention to report pesticide contamination by providing practical, persuasive, and normative information about poisoning and the hotline. Different media and participatory formats were used to deliver the messages in a vivid and engaging way. Materials were distributed, such as posters and stickers, and attendees were encouraged to display or share these with others, and discuss the issue with their friends and neighbors (Appendix S1).

To observe changes in knowledge and psychological outcomes, we conducted 3 questionnaire surveys in the village at 3 different times: before the intervention, 2 weeks after the intervention, and 6 months after the intervention (Table 1). The presence of outside researchers may increase the salience of the research topic, causing respondents to reevaluate their beliefs, communicate with others, or seek further information. We considered it necessary to be able to control for this effect. Therefore, in the first survey, we randomly selected half of the village for exclusion. In surveys 2 and 3, we aimed to interview all adults in the village. We modeled the data in conjunction with social-network data collected previously. The study was approved by the University of Edinburgh School of Geosciences ethical review board, and all participants gave their informed consent. All survey instruments were piloted with a small sample of respondents in another village.

Network data

In September 2017 (Table 1), we collected social network data through a survey capturing ~91% of adults in the village. We measured a general social network, aiming to capture habitual social contact (i.e., time spent together) between adult villagers (>18 years old). To construct this network, we measured ties of 3 kinds: coresidence ties between adults in the same household, household visits, and household visitors. For coresidence ties, we conducted a household census and verified this with information provided by the village chief. We assumed that ties existed between adults living in the same household (i.e., that individuals within a household mix and communicate homogenously). We measured the other ties with a name-generator survey: respondents were asked to nominate others whom they visit at home or who come to visit them at home (Knoke & Yang, 2011). Extensive prior qualitative research suggests that these ties are likely to comprise the bulk of everyday social interaction in the village, making them a key conduit for both information and influence (see Appendix S1). We remeasured the social network with survey 3 (see below).

Psychological and knowledge data

The intervention outcomes we measured through our surveys are psychological constructs from the TPB: intentions, attitudes, perceived control, perceived descriptive norms, and perceived injunctive norms. Reporting poisoning is likely to be a planned behavior because it requires conscious forethought to retrieve the hotline number and make the call from an appropriate location. Because the number of poisoning events in the vicinity of any village was likely to be very low, measuring actual reports of poisoning events was not a useful indicator of behavioral change, hence the use of intention to report as our outcome measure. (Two events were confirmed at the study site in the 4 years prior to introduction of the hotline, and no events were reported during the study period.) We measured each construct (intention, attitudes, perceived control, and perceived descriptive and injunctive norms) with multiple 5-point Likert scales, which were summed to produce continuous

measures (Appendix S1). We assessed the internal consistency of the measures for each construct using Cronbach's alpha.

Following the intervention, we also measured knowledge of key intervention messages based on 12 questions related to 3 components of the intervention (Appendix S1). We asked questions in an open-ended manner, recorded the response verbatim, and subsequently coded answers that correctly referred to intervention messages. We then summed correct responses to arrive at a knowledge score. Questions were worded so as not to give away information for future surveys. We asked respondents to describe the source of their information and coded responses into the following categories: relatives, other people, and intervention materials.

Analytical approach

All analyses were conducted in R 4.02 (R Core Team, 2017). We used LMMs to explore variation in outcomes over time and between groups. We used SAOMs to determine whether the network predicted outcomes.

Missing data imputation

We used analyses of complete cases and of multiply imputed data to address missing outcome data (Pepinsky, 2018). We generated 20 imputations with predictive mean matching in the mice package (van Buuren & Groothuis-Oudshoorn, 2011). Twenty was considered a good compromise between robustness and computation time (Krause et al., 2018). Furthermore, model estimates did not vary greatly between 5 and 20 imputations, suggesting they were robust to the number of imputations. The imputation model included all knowledge and psychological constructs for all waves and all demographic and other variables used in the analysis models. We graphically checked for implausible imputations (Nguyen et al., 2017). For SAOMs, we took the imputations from mice as a starting point and then carried out 20 joint multiple imputations of the network and outcomes taking into account the model specification (Krause et al., 2018). For full details, see Appendix S1.

Changes in knowledge and psychological outcomes

To explore variation in the data, we fitted LMMs. First, we examined how intervention outcomes changed over time among attendees and nonattendees (hypotheses H1, H2, H3, and H5) by modeling the interaction between attendance and time period as predictors. We used linear hypothesis testing in the car package to compare the effects of time on different groups and calculated standard errors with the delta method (Fox & Weisberg, 2019). Second, we examined the relation between knowledge and psychological outcomes (H6) in 2 ways: with the total knowledge score and with knowledge of the 3 intervention components as separate predictors (hotline, story, pledge). All LMMs included the following control variables; gender, age (normalized), pesticide use, household wealth, par-

ticipation in survey 1, and participation in the conservation agriculture program Ibis Rice (www.ibisrice.com). Respondent identity was included as the random effect. We pooled estimates modeled on each imputed data set (van Buuren, 2018). Finally, to assess the psychological determinants of intention to report poisoning, we fitted a generalized linear model (GLM) for the TPB at each survey wave.

Stochastic actor-oriented models

To understand how the social network influenced changes in knowledge and behavior (H4, H7, and H8), we fitted SAOMs, implemented in the R package RSiena (Ripley et al., 2020). Typically, SAOMs model network–behavior coevolution; changes are driven by the simulated decisions of individual actors in continuous time. The simulations are calibrated to empirical observations of the network or behavior at fixed time points (Greenan, 2015; Snijders, 2017; Snijders et al., 2010). By setting the rate parameters at a low value, SAOMs can also be used to model static networks (Block et al., 2016; Snijders & Steglich, 2015). We fitted SAOMs with the measured social network, which is static, with 3 sets of (dynamic) outcomes data. We used forward estimation to build the model, including theoretically important effects, and then included effects related to our research questions (Ripley et al., 2020) until the models included as many effects of interest as possible, had an overall convergence ratio under 0.2, and adequately fitted the data as observed using the visual method described by Wang et al. (2020) (Appendix S1). We performed a robustness check by repeating our models with the partially remeasured network data in survey 3. In this network, individuals not surveyed in survey 3 retained their network ties from survey 1 (Appendix S1).

First, we modeled whether having knowledgeable social peers predicted diffusion of knowledge (H4). We used the diffusion-of-innovations extension to the SAOM (Greenan, 2015) in which knowledge is binary (i.e., an individual has knowledge or does not) and does not decrease. (We did observe some loss of knowledge over time [Figure 4].) With the first survey, we assumed that only those who participated in the intervention had knowledge. We modeled information diffusion in relation to the habitual social contact network and with the 3 types of social ties (i.e., coresidence, visits, and visitors) separately. In each model, the effect of interest was the total network exposure to information (i.e., the total number of peers with knowledge at each time point). No further effects were included because this would have decreased model fit or reduced convergence.

Next, we used SAOMs to examine peer influences on psychological outcomes. We separately modeled 3 social-influence pathways with the habitual social contact network (modeling ties separately did not result in adequate model convergence). Pathways were whether individuals tended to change their behavioral intention to match their peers (H7); whether perceptions of descriptive norms varied with the intentions of an individual's peers (H8); and whether perceptions of injunctive norms varied with the attitudes of an individual's peers (H8). For the first
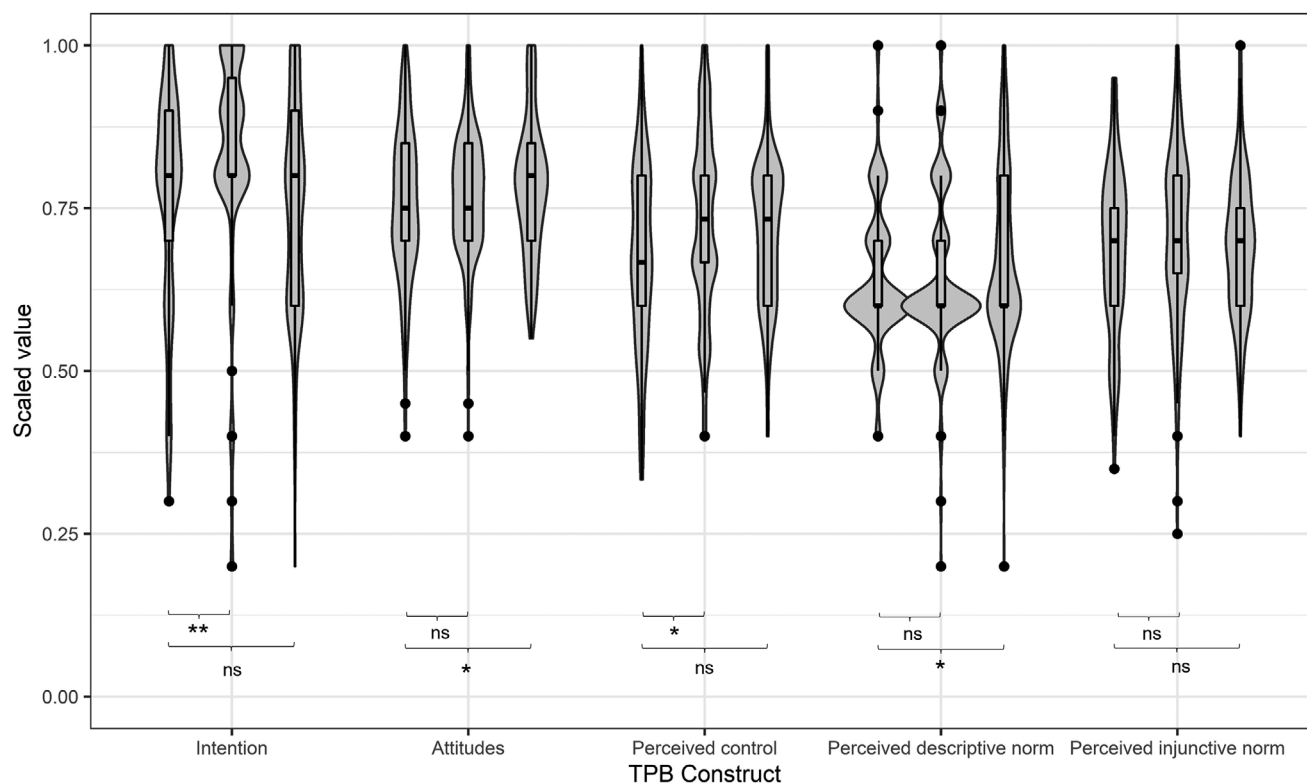
FIGURE 2 Changes in psychological outcomes following a social marketing campaign to promote a hotline for reporting wildlife poisoning in Cambodia measured, in 3 separate surveys, based on constructs from the theory of planned behavior (TPB): intention to report poisoning, attitudes toward reporting, perceived ability to report poisoning, perceived descriptive norms, and perceived injunctive norms (black horizontal line, mean; box, SD; whiskers, 95% CIs; dots, outliers). Each construct is measured with a set of questions answered on a 5-point Likert scale. The range of values for each construct differs, so they are scaled from 0 to 1 to enable visual comparison. Significance levels are for differences between surveys, estimated using linear mixed effect models ($*p < 0.5$, $**p < 0.1$, $***p < 0.001$, ns, not significant)

pathway, we modeled social influence with the average-similarity effect. This effect is defined as the average of the similarity scores between an individual's intention and that of the others to whom they are tied. The second and third pathways examined the effect of peer intentions or attitudes on an individual's perceived norms. We used the alters-covariate-average effect, which is the product of the individual's perceived norm (i.e., descriptive or injunctive norm) and the average value of covariates (i.e., intention or attitudes) for those with whom they are connected.

These 3 models also included the effect of knowledge about the intervention. We included a time dummy variable to account for heterogeneity in effects between periods (Lospinoso et al., 2011). This dummy variable would indicate whether psychological outcomes tended to improve or decline between surveys 2 and 3. We examined the interaction between this variable and social influence effects to determine whether social influence was stronger between surveys 1 and 2 or surveys 2 and 3. We also examined the interaction between knowledge and social influence. The first 2 models included effects controlling for gender, age, wealth, participation in Ibis Rice, pesticide use, and in-degree and out-degree (i.e., the number of incoming or outgoing connections an individual has in the network, respectively). The latter effects express the tendency for

individuals with higher numbers of incoming or outgoing connections, respectively, to increase their behavioral outcome over time. Due to difficulties with SAOM convergence (see Ripley et al., 2020), only in-degree and out-degree were included as control effects in the third model.

RESULTS

Overall, 400 adult residents from 156 households participated in this study, of which 365 were included in the measured social network and SAOMs. In total, the village social network comprised 1637 asymmetric ties, of which 650 (40%) were coresidence ties. The 3 surveys had 181 (50% of the network), 283 (78%), and 192 (53%) respondents, respectively (Table 1). Before the intervention, attitudes and intention to report poisoning were largely positive but varied widely, whereas perceptions of control and perceptions of norms were less positive (Figure 2). Initially, no outcome variable differed significantly between those who would later attend the intervention and others (Appendix S1). In all 3 surveys, intention was significantly correlated with all TPB variables except perceptions of descriptive norms (Figure 3). Attitudes (att) remained the most important predictor throughout (GLM survey 3: $\beta_{att} = 0.25$, SE
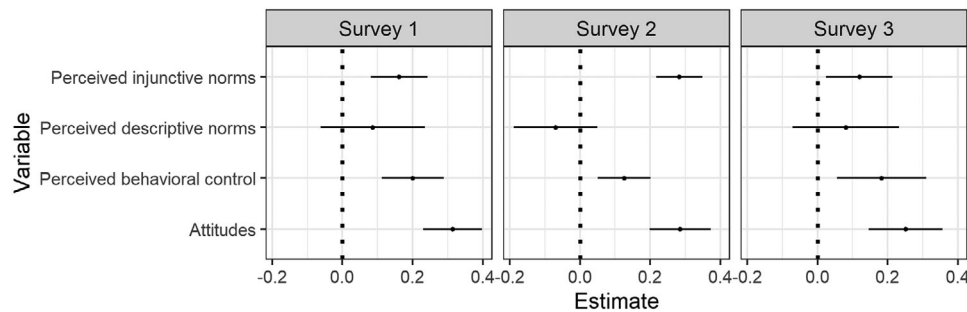
FIGURE 3 Estimates of the relationships of attitudes, descriptive norms, injunctive norms, and behavioral control with intention to report poisoning of waterholes (black horizontal lines, 95% CIs). The coefficients were estimated from generalized linear models with complete case data at each survey

0.05, $p < 0.01$), whereas the correlation with injunctive norms (inj) was higher in survey 2 ($\beta_{inj} = 0.28$, SE 0.03, $p < 0.01$) than in survey 3 ($\beta_{inj} = 0.12$, SE 0.04, $p = 0.02$). Analysis of the imputed data showed similar patterns (Appendix S1).

Participant's knowledge of the intervention (H1)

In survey 2, intervention attendees could recall on average 58% (SD 25) of messages from the intervention and 48% (SD 27) in survey 3, across all imputations.

Participant's beliefs and intentions (H2)

Survey 2 showed that participants increased their intention over time to report poisoning ($\beta_{par+w2} = 1.19$, SE 0.39, $p < 0.01$). Perceptions of injunctive norms ($\beta_{par+w2} = 1.76$, SE 0.55, $p < 0.01$) and perceptions of control ($\beta_{par+w2} = 1.41$, SE 0.44, $p < 0.01$) also increased significantly between surveys 1 and 2, but attitudes and perceptions of descriptive norms did not. Analysis of the multiply-imputed data showed clear evidence only for more positive perceptions of injunctive norms in the short term ($\beta_{par+w2} = 1.76$, SE 0.50, $p < 0.01$) (Appendix S1). However, in survey 3, none of the TPB variables differed significantly from survey 1.

Other residents' knowledge of the intervention (H3)

Nonattendees also learned about the intervention. In survey 2, at least 55 individuals (15% of nonattendees) had some knowledge about the intervention. Across all imputations, an average of 79 individuals (SD 5.1) were knowledgeable, recalling on average 18% (SD 13) of messages. In survey 3, at least 141 adult residents (39% of the whole sample, including attendees) could recall information from the event (Figure 4). Across all imputations, an average of 148 respondents (SD 8.6) were knowledgeable, recalling on average 32% (SD 22%) of messages

shared. Information about the 3 key components of the intervention spread differently. On average in survey 3, 50 (SD 5.6), 52 (SD 7.4), and 72 (SD 9.2) nonparticipants were knowledgeable about the hotline, pledge, and film, respectively, across all imputations.

Information flow (H4)

Of nonattendees with knowledge, 27% stated that they learned about the intervention from relatives, 10% reported learning about the intervention through disseminated materials (e.g., stickers with the hotline number on them), and 8% learned about it through communication with others in the village. However, 52% could not recall where they had received the information. The SAOMs showed that having an additional social tie with an individual knowledgeable about the intervention increased the probability that a respondent would become knowledgeable by a factor of 1.39 (i.e., exponent of the effect size was $e^{0.332}$, SE 0.12) (Appendix S1). When modeling different ties separately, only exposure within the household was significant. Having an additional household member with knowledge of the intervention increased the probability that an individual would become knowledgeable by a factor of 1.87 ($e^{0.627}$, SE 0.26) (Appendix S1).

Other residents' beliefs and intentions (H5)

Changes in outcomes were also observed among residents who did not attend the intervention (Appendix S1). Survey 2 showed that intention to report poisoning ($\beta_{w2} = 0.55$, SE 0.18, $p < 0.01$) and perceptions of control ($\beta_{w2} = 0.79$, SE 0.21, $p < 0.01$) improved over time. In survey 3, intention to report poisoning was no longer different from survey 1, but perceptions of control remained more positive ($\beta_{w3} = 0.67$, SE 0.22, $p < 0.01$). Attitudes ($\beta_{w3} = 0.58$, SE 0.25, $p = 0.02$) and perceptions of descriptive norms ($\beta_{w3} = 0.41$, SE 0.14, $p < 0.01$) were also more positive in survey 3. Analyses of the imputed data sets suggested similar patterns of change for each variable, except that perceived control did not change (Appendix S1).
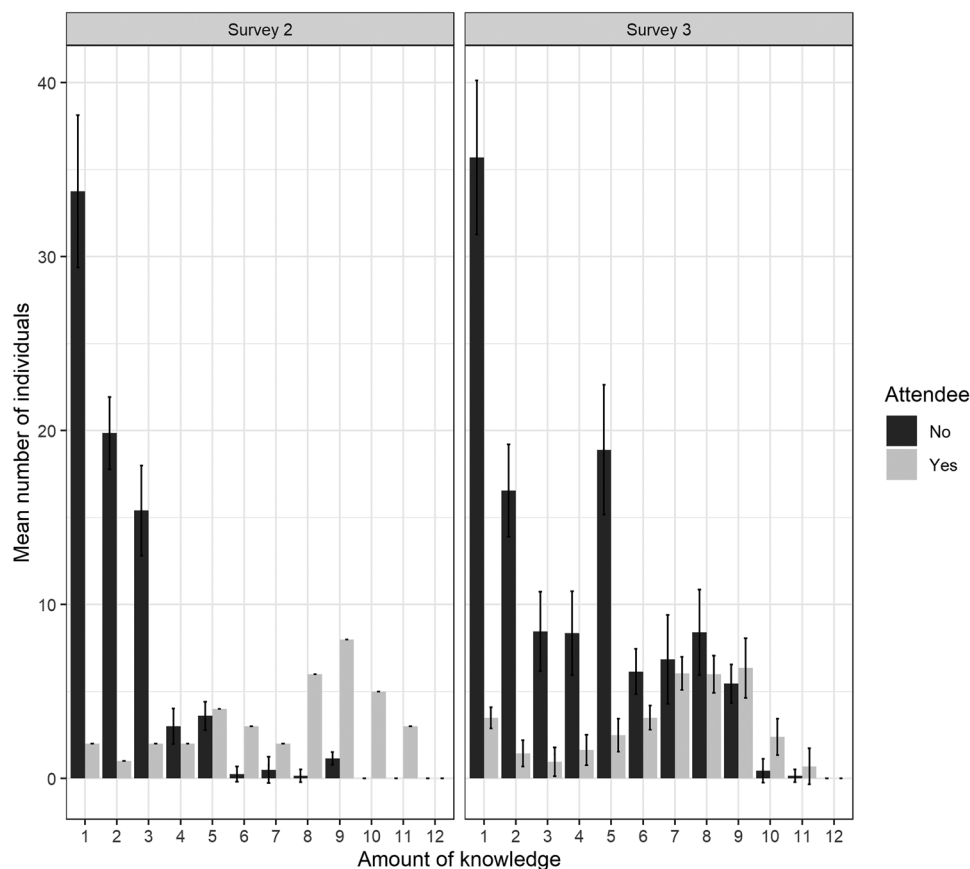
FIGURE 4 Mean number of individuals with each level of knowledge (from 1, least knowledge, to 12, most knowledge) about the campaign to promote a hotline for reporting wildlife poisoning across 20 imputations (gray, participants in intervention; black, nonparticipants; whiskers, SE). In the survey before the intervention (survey 1), no respondents had knowledge because the assessed messages were designed to be unknowable to those not attending the event. Survey 2 was conducted 2 weeks after the intervention, and survey 3 was conducted 6 months after the intervention. There were 248 nonparticipants who did not have any knowledge about the intervention (SD 5), 1 participant (SD 0) in survey 2, and 213 nonparticipants (SD 8) and 4 participants (SD 1) in survey 3. These individuals are not shown in the figure

Effect of knowledge on intention (H6)

In LMMs, knowledge was associated with more positive behavioral intention ($\beta_{kno} = 0.14$, SE 0.06, $p = 0.02$), attitudes ($\beta_{kno} = 0.31$, SE 0.08, $p < 0.01$), perceptions of control ($\beta_{kno} = 0.23$, SE 0.07, $p < 0.01$), perceptions of descriptive norms ($\beta_{kno} = 0.09$, SE 0.04, $p = 0.04$), and perceptions of injunctive norms ($\beta_{kno} = 0.32$, SE 0.09, $p < 0.01$). In imputed data, the effect of knowledge on intention and perceptions of descriptive norms was not significant. Modeling knowledge of each intervention component separately, the only significant correlation was between knowledge about the hotline and perceived injunctive norms ($\beta_{hot} = 0.38$, SE 0.14, $p < 0.01$). However, SAOM models showed that knowledge was not a significant predictor of changes in intention, when accounting for social influences (model 1, effect 3 in Table 2).

Peer influences on intention (H7)

The SAOM estimates for social influence models are presented as log-odds ratios in Table 2. Changes in intention to report poisoning were predicted by the intentions of social peers (model 1, effect 1). The significant average-similarity effect indicates a tendency for individual intentions to become more similar to the average of their peers over time. Residents were 1.24 times more likely to adjust their intention in this way than not to change (i.e., exponent of the effect size divided by the number of levels of the behavior $= e^{\frac{1.713}{8}}$). This effect did not vary over time or with knowledge of the intervention (interaction effects 5 and 6). There was also a tendency to reduce intention between surveys 2 and 3 (effect 4), which was not accounted for by other effects, indicating a potential weakening of the intervention's effects over time.

TABLE 2 Summary results from 3 stochastic actor-oriented models[*] of the effect of the social network on outcomes related to a conservation intervention aimed at halting poisoning of waterholes as a means of procuring wild meat by promoting reporting through a hotline

Model effects	Change in intention, estimate (SE)		Perceived descriptive norm, estimate (SE)		Perceived injunctive norm, estimate (SE)	
Effect						
1. Average similarity	+1.713	(0.542)	–	–	–	–
2. Average covariate alter (intention for model 2 or attitudes for model 3)	–	–	–0.004	(0.036)	–0.012	(0.013)
3. Intervention knowledge	+0.036	(0.022)	+0.064	(0.029)	+0.047	(0.015)
4. Period 2	–0.222	(0.048)	+0.099	(0.068)	–0.049	(0.028)
Interaction effects						
5. Social influence × knowledge	+0.381	(0.487)	–0.011	(0.029)	+0.006	(0.013)
6. Social influence × period 2	+0.448	(0.699)	+0.003	(0.074)	–0.036	(0.027)
Control effects						
7. Linear shape	+0.035	(0.065)	+0.039	(0.091)	–0.021	(0.040)
8. Quadratic shape	–0.034	(0.011)	–0.180	(0.015)	–0.048	(0.003)
9. In-degree	–0.001	(0.009)	+0.015	(0.013)	+0.014	(0.005)
10. Out-degree	+0.010	(0.014)	–0.010	(0.019)	–0.006	(0.008)
11. Age	+0.002	(0.002)	+0.002	(0.002)	–	–
12. Wealth	–0.021	(0.023)	–0.019	(0.030)	–	–
13. Gender	+0.0001	(0.040)	–0.013	(0.062)	–	–
14. Conservation agriculture	+0.040	(0.040)	+0.140	(0.068)	+0.029	(0.031)
15. Pesticide use	–0.007	(0.047)	+0.009	(0.069)	–	–

*The 3 models examine change in intention to report poisonings (model 1), perceived descriptive norms (model 2), and perceived injunctive norms (model 3).

Peer influence mechanisms (H8)

Peer intentions and attitudes did not predict changes in perceived norms (Table 2, models 2 and 3, effect 2), but knowledge of the intervention did tend to improve perceptions (effect 3). There was also a tendency for perceived injunctive norms to decline between surveys 2 and 3. Participants in Ibis Rice were also more likely to gain more positive perceptions of descriptive norms.

DISCUSSION

Using state-of-the-art models of network–behavior dynamics, longitudinal behavioral data collected across an entire village, and an innovative study design, we determined how social networks shaped the outcomes of an important conservation intervention. Specifically, a social marketing event aiming to reduce wildlife poisoning by encouraging use of a reporting hotline had spillover effects beyond the individuals targeted (i.e., the intervention participants) that were mediated by a village social network representing habitual social contact. We observed a significant improvement in intention to report poisoning throughout the entire village after 2 weeks, and information from the intervention spread widely through the village. However, despite lasting changes in some psychological outcomes, such as perceived behavioral control and attitudes, the intervention failed to change behavioral intentions in the long term. Evidence from SAOMs suggested that both the improvement and subsequent decline in intention were driven by the social influences of network peers, rather than by individuals learning about the intervention (Table 2). The social network may therefore have initially promoted and subsequently undermined the intervention as residents sought to align their intentions with those of their social peers.

The intervention included dissemination of information and materials to facilitate learning about poisoning and the hotline because this was considered an essential precondition for behavior change. This information flowed relatively well for a small intervention. After 6 months, the number of residents knowledgeable about the intervention more than tripled. Much of this flow could be predicted by household coresidence ties, not social visiting ties, suggesting that reaching at least one member of as many households as possible could be an effective information dissemination strategy in this context. Our measured social network did not adequately capture the interactions through which information might have spread between households. This highlights the difficulty in capturing and measuring the weak interactions through which information spreads in physical communities (Granovetter, 1973), which may include brief encounters with strangers or even overhearing others' conversations.

Knowledge of the intervention was correlated with more positive intentions, attitudes, perceived control, and perceptions of social norms in linear models. However, dynamic SAOMs showed that learning about the intervention did not lead to changes in behavioral intention (Table 2). Instead, individuals with more positive attitudes toward or perceptions of reporting may have actively sought out information or were better able to recall it (Valente et al., 1998). In support of this interpretation, we observed no improvement in attitudes in the short term despite widespread dissemination of information. Instead, these models showed that the influences of network peers predicted changes in intention as individuals improved or reduced their intention to be more similar to their peers. After learning about the hotline, residents may have sought out social cues to determine whether reporting was a socially appropriate behavior (Prentice & Paluck, 2020). Rather than driving behavioral change, interpersonal communication about the new behavior may ultimately have reinforced the status quo, pushing residents to conform with existing levels of behavior. This contradicts evidence from elsewhere that increased communication about a new conservation behavior tends to increase behavioral change (Green et al., 2019).

Although our models indicated that social influences were occurring, we could not establish the cognitive mechanisms underlying this effect because peer intentions did not appear to drive changes in perceptions of descriptive norms and peer attitudes did not influence perceptions of injunctive norms (Cialdini et al., 1991). Perhaps individuals are misperceiving the attitudes or intentions of their peers because reporting poisoning is both a rare and potentially sensitive behavior, which makes observation of others' behavior or communication about the behavior uncommon (Prentice & Miller, 1996). In the absence of clear social cues from their network peers, residents may have used other sources of information to evaluate social norms, such as cues from outside the village, on social media, or from village leaders. This might explain why knowledge about the intervention tended to drive more positive norm perceptions, indicating that the intervention messages were appropriately framed (Kusmanoff et al., 2020). For example, the short film and pledging ceremony were both designed to alter norm perceptions (Bicchieri, 2017). But, our measures of the perceived descriptive norm had a low internal consistency, suggesting that we did not adequately measure the underlying construct.

The peer-influence effects we observed for behavioral intention may have occurred through other processes. For example, individuals may resolve ambiguity around reporting poisoning by deferring to the opinions of their peers, without updating their perceived norms (i.e., informational influence [Wooten & Reed II, 1998]). Alternatively, there may be important but unobserved variables, such as personality traits, that tend to be similar for socially close individuals and that are challenging to discount in observational studies (Shalizi & Thomas, 2011). Alternatively, individuals' norm perceptions may be informed by individuals with whom they did not have direct ties represented in our social network (Shepherd, 2017). For example, they may be looking to local leaders, or others to whom they are weakly tied, rather than their direct peers (Lee & Kronrod, 2020). Further research to understand which referent groups are salient in perceptions of norms is therefore critical (Prentice & Paluck, 2020).

Despite successfully diffusing information necessary for behavior changes to occur (such as information about the hotline) and using appropriate message framings to influence norm perceptions, attitudes, and perceptions of control, the intervention failed to change intentions in the long term. The countervailing effect of social influence indicated that use of the reporting hotline is a complex contagion, which, unlike information, requires social reinforcement for adoption (Centola & Macy, 2007). This is also likely to be the case for many conservation behaviors, which are often related to provision of public or common goods (Turaga et al., 2010).

We also observed a tendency for intentions to decrease in the long term independent of other effects. Although intention is measured in relation to a specific context and is theoretically semi-stable, it may be that the issue became less salient over time due to the rarity of poisoning events. The observed changes in knowledge and psychological outcomes provide the conditions necessary for future behavior change to occur. To sustain these impacts and create behavior change in the long term, continued engagement with a community, consisting of repeated interventions, and other efforts at gradually influencing relevant social structures (Brooks et al., 2013) or exploiting social influences are needed (Centola, 2018; Valente, 2012). This could involve working with highly connected opinion leaders (Valente & Pumpuang, 2007), small groups of socially close individuals (Centola, 2018), or even forming new ties between receptive individuals (Contractor & DeChurch, 2014). In Cambodia, antipoisoning interventions could be integrated with broader social interventions, such as the Ibis Rice conservation agriculture program, that aim to influence agricultural and conservation decision-making (Clements et al., 2020). Furthermore, such strategies may alter the structures of social networks in the long term, potentially producing more enabling social contexts (de Lange et al., 2019).

Although conservation scientists are increasingly interested in relational processes, little research has looked at how these processes operate in real-world conservation contexts (de Lange et al., 2019; Groce et al., 2019). Using an innovative network modeling approach (Greenan, 2015; Steglich et al., 2010), we interrogated the social influence processes that followed a conservation intervention. Our results highlight the critical importance of social relations in shaping conservation behaviors. In keeping with the theory of complex contagions, we found that information flow occurred more easily than behavior change and did not lead straightforwardly to change in intention (Centola, 2018; Schultz, 2002). Furthermore, as conservation practitioners begin to incorporate relational insights into their intervention, such as the targeting of network central individuals (Mbaru & Barnes, 2017), longitudinal studies, such as ours, will be needed to evaluate these approaches. This will support better understanding of the dynamic processes of social change and the design of more effective intentions (de Lange et al., 2019; Ferraro & Pattanayak, 2006).

ORCID

Emiel de Lange https://orcid.org/0000-0002-5853-3657
E.J. Milner-Gulland https://orcid.org/0000-0003-0324-2710
Aidan Keane https://orcid.org/0000-0002-9704-5576

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