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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 behavioural interventions in conservation as network processes such as information flows and social influence can enable behaviour change to spread beyond a targeted group. We investigated these mechanisms using social network data and longitudinal behavioural data from a conservation intervention in Cambodia, and Stochastic Actor-Oriented Models. The intervention initially targeted ~11% of the village population, but knowledge of the intervention reached ~40% of the population within six months. The likelihood of an individual having this knowledge nearly doubled with each additional knowledgeable household member. In the short term, there was also a modest, but widespread improvement in pro-conservation behavioural intention, but this did not persist into the long term. Estimates from network models suggest that the influences of social peers, rather than knowledge of the intervention, were driving changes in intention and contributed to the failure to change behavioural intention in the long term. Our results point to the importance of accounting for the interaction between networks and behaviour when designing conservation interventions.

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Introduction

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

Human behaviour is shaped by a wide range of beliefs and perceptions that individuals hold about the world. The Theory of Planned Behaviour, a widely-used model for understanding intentional behaviours in individuals, posits that intentions to act in a particular way within a particular context are dependent on attitudes (i.e. is the behaviour good?), perceptions of control (i.e. am I able to do it?), and perceived social norms (Ajzen, 1991). Perceived norms can further be described as descriptive (i.e. how do others behave?) or injunctive (i.e. how do others expect me to behave?), 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 two important ways (Contractor & DeChurch, 2014; de Lange et al., 2019). Firstly, as individuals communicate and share information about the world, this information will alter 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 social programme, attitudes towards 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 upon (Pornpitakpan, 2004; Faraji-Rad et al., 2015). 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 gaining momentum as more individuals adopt (Rogers, 2003). However, this theory has been critiqued because it conceptualises communication as a one-way process, and is focused on the factors that enable diffusion and not 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 emphasises the central role of social information (Centola, 2010). This theory distinguishes between simple contagions which are transmitted in one direction through a single exposure, such as information, and complex contagions which require social reinforcement/influence or multiple exposures in a social network to diffuse. Among other reasons, many behaviours are 'complex' because there are social risks involved with adoption or because they require coordination between adopters (Centola, 2018). Information about and perceptions of the behaviour or attitudes of referent others in the individual's social networks are therefore critical and can influence behaviour through changing perceived norms (McDonald & Crandall, 2015; Bicchieri, 2017). When norms and the behaviours of social referents are not supportive of a new practice, individuals may tend to comply or conform and diffusion will fail, even if they receive positive information about the practice and hold positive attitudes towards it (Cialdini & Goldstein, 2004). Conversely, positive social influences can be a driver of widespread behaviour change (Kim et al., 2015; Nakano et al., 2018), and are therefore a second important network process.

Most network studies aiming to inform conservation practice use observations of social relations and behaviour at a single point in time, usually before the intervention takes place (Groce et al., 2018). This data is used to predict how an intervention might harness social influence, such as by identifying influential individuals to target (Mbaru & Barnes, 2017) or to delimit relevant social groupings (Crona & Bodin, 2006). However, social change is a temporal process and to untangle the mechanisms shaping behaviour there is a need to move beyond cross-sectional approaches and adopt a longitudinal perspective (Robins, 2015; Shalizi & Thomas, 2011; Steglich, Snijders & Pearson, 2010). Such studies have rarely been conducted in conservation.

In this study, we aim to understand how two important network processes – information flow and social influence - mediate the success or failure of a conservation intervention taking place in a part of Cambodia where 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 measured the village's social networks, then conduct a longitudinal analysis of behaviour change by collecting survey data at three time points before and after the intervention.

We hypothesised that: intervention participants would gain knowledge about reporting (H1), which would alter their beliefs and intention to report poisoning (H2). Moreover, other residents would also become knowledgeable about the intervention (H3), because they received information about the intervention through their social networks (H4). Other residents would also 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).

Furthermore, this social influence would occur through changing perceptions of social norms (H8). We use 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 South-east 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. Research has revealed that poisoning is a method for harvesting wild meat practiced by some local farmers and youths. However, most residents do not approve of this practice due to risks to 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 have 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 to 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 information about poisoning and the hotline that was expected to alter their beliefs and perceptions. Different media and participatory formats were used to deliver the messages in a vivid and engaging way. Materials with practical and persuasive information were distributed, which attendees were encouraged to display or share with others, such as posters and stickers, and they were encouraged to discuss the issue with their friends and neighbours (see SM1 & Figure S1).

To observe changes in knowledge and psychological outcomes, we conducted questionnaire surveys in the village at three time points before and after the intervention. The presence of outside researchers may increase the salience of the research topic, causing respondents to re-evaluate 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 wave, we excluded a randomly selected half of the village. In all other waves, we aimed to interview all adults in the village. We modelled 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). To construct this network, we measured ties of three kinds: 1) co-residence ties between adults in the same household, 2) household visits, and 3) household visitors. For co-residence 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 using 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 suggested that these ties are likely to comprise the bulk of everyday social interaction in the village, therefore making them a key conduit for both information and influence (see SM2). We re-measured the social network at survey wave 3 (see below).

Psychological & knowledge data

We measured outcomes in three waves: 1) two weeks before the intervention, 2) two weeks after the intervention, and 3) six months later, in August 2019 (Table 1). Our measured intervention outcomes are psychological constructs from the TPB; intentions, attitudes, perceived control, perceived descriptive norms, and perceived injunctive norms. Reporting is likely to be a planned behaviour 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 is likely to be very low (two events were confirmed at the study site in the four years prior to introduction of the hotline and no events were reported during the study period), measuring actual reports of poisoning events is not a useful indicator of behavioural change, hence the use of intention to report as our outcome measure. We measured each construct using multiple five-point Likert scales, which were summed to produce continuous measures (see SM2). 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 using twelve questions related to three components of the intervention (see SM1). 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 test if the network predicted outcomes.

Missing data imputation

We used analyses both of complete-cases and of multiply imputed data to handle missingness in outcomes data (Pepinsky, 2018). We generated 20 imputations using 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, we observed that model estimates did not vary greatly between 5 and 20 imputations, suggesting they are 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 SM3&4.

Changes in knowledge and psychological outcomes

To explore variation in the data, we fitted LMMs. First, we examined how intervention outcomes changed over time amongst attendees and non-attendees (hypotheses H1 & H2) by modelling 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 using the delta method (Fox & Weisberg, 2019). Second, we examined the relation between knowledge and psychological outcomes (H3), in two ways: with the total knowledge score, and with knowledge of the three intervention components as separate predictors (hotline, story, pledge). All LMMs included the following control variables; gender, age (normalised), pesticide use, household wealth, participation in survey wave 1, and participation in the conservation agriculture programme ‘Ibis Rice’ (www.ibisrice.com). Respondent identity was included as the random effect. We pooled estimates modelled on each imputed dataset (van Buuren, 2018). Finally, to assess the psychological determinants of intention to report poisoning, we fitted a generalised 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 behaviour (H3-5) we fitted SAOMs, implemented in the R package “RSiena” (Ripley et al., 2020). SAOMs typically model network-behaviour co-evolution, where changes are driven by the simulated decisions of individual actors in continuous time. The simulations are calibrated to empirical observations of the network/behaviour at fixed time points (Snijders et al., 2010; Greenan, 2015; Snijders, 2017). By setting the rate parameters at a low value, SAOMs can also be used to model static networks (Snijders & Steglich, 2015; Block et al., 2016). We fitted SAOMs using the measured social network, which is static, with three waves of (dynamic) outcomes data. We used forward estimation to build the model; including theoretically important effects, and then including 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) (see SM5). We perform a robustness check by repeating our models using the partially re-measured network data in wave 3. In this network, individuals not surveyed in wave 3 retain their network ties from wave 1 (see SM3).

First, we modelled whether having knowledgeable social peers predicts diffusion of knowledge (H3). We used the ‘Diffusion of Innovations’ extension to the SAOM (Greenan, 2015) where knowledge is binary (i.e., does the individual have any knowledge?) and non-decreasing. In the first wave, we assumed that only those who participated in the intervention had knowledge. We modelled information diffusion in relation to the habitual social contact network, and separately with the three types of social tie (i.e., co-residence, 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 as this decreased model fit or reduced convergence.

Next, we used SAOMs to examine peer influences on psychological outcomes. We separately modelled three social influence pathways, using the combined network: First, do individuals tend to change their behavioural intention to match their peers (H4)? Second, do perceptions of descriptive norms vary with the intentions of an individual’s peers (H5)? And third, do perceptions of injunctive norms vary with the attitudes of an individual’s peers (H5)? For the first model, we modelled social influence using the ‘average similarity’ effect. This effect is defined as the average of the similarity scores between an individual’s behaviour and that of the others to whom they are tied. The second and third models examined the effect of peer intentions or attitudes on an individual's perceived norms. We used the 'alter's covariate average' effect; the product of the individual's perceived norm (i.e., descriptive or injunctive norm) and the average covariate values (i.e. intention or attitudes) of those with whom they are connected.

These models also included the effect of knowledge about the intervention. We included a time dummy variable to account for heterogeneity in effects between time periods (Lospinoso et al., 2011). This dummy variable would indicate whether psychological outcomes tended to improve or decline in period 2. We interacted this variable with the social influence effects to determine if social influence is stronger in either period. We also interacted knowledge with social influence. The first two models included effects controlling for gender, age, wealth, participation in Ibis Rice, pesticide use, in-degree and out-degree. The latter effects express the tendency for individuals with higher numbers of incoming or outgoing connections, respectively, to increase their behavioural 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 co-residence ties. The three waves 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, while 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 (Tables S5:S9). In all three waves, intention was significantly correlated with all TPB variables except perceptions of descriptive norms (Figure 3). Attitudes remained the most important predictor throughout (GLM, β_{att}=0.25, SE=0.05, p<0.01, in wave 3), while the correlation with injunctive norms was higher in wave 2 (β_{inj}=0.28, SE=0.03, p <0.01), than in wave 3 (β_{inj}=0.12, SE=0.04, p=0.02). Analysis of the imputed data showed similar patterns (Table S10).

H1: Participant's knowledge of the intervention

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

H2: Participant's beliefs and intentions

Participants increased their intention to report poisoning in wave 2 (β_{par+w2}=1.19, SE=0.39, p<0.01). Perceptions of injunctive norms (β_{par+w2}=1.76, SE=0.55, p<0.01) and perceptions of control (β_{par+w2}=1.41, SE=0.44, p<0.01) also improved significantly, but attitudes and perceptions of descriptive norms did not. Analysis of the multiply-imputed data only showed clear evidence for more positive perceptions of injunctive norms in the short term (β_{par+w2}=1.76, SE=0.50, p<0.01, Table S8). However, in wave 3, none of the TPB variables differed significantly from wave 1.

H3: Other residents' knowledge of the intervention

Non-attendees also learned about the intervention. In wave 2, at least 55 individuals (15% of non-attendees) 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 wave 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 three key components of the intervention spread differently; on average in wave 3, 50 (SD=5.6), 52 (SD=7.4), and 72 (SD=9.2) non-participants were knowledgeable about the hotline, pledge, and film, respectively across all imputations.

H4: Information flow

Of non-attendees 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 printed), and 8% through communication with others in the village. However, 52% could not recall where they had received the information. 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. the exponent of the effect size $= e^{0.332}$, SE=0.12, Table S11). When modelling 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, Table S11).

H5: Other residents' beliefs and intentions

Changes in outcomes were also observed amongst residents who did not attend the intervention (Tables S5:S9). In wave 2, intention to report poisoning (β_{w2}=0.55, SE=0.18, p<0.01), and perceptions of control (β_{w2}=0.79, SE=0.21, p<0.01) were improved. In wave 3, intention to report poisoning was no longer different from wave 1, but perceptions of control remained more positive (β_{w3}=0.67, SE=0.22, $p<0.01$). Attitudes (β_{w3}=0.58, SE=0.25, $p=0.02$) and perceptions of descriptive norms (β_{w3}=0.41, SE=0.14, $p<0.01$) were also more positive in wave 3. Analyses of the imputed datasets suggested similar patterns of change for each variable, except that perceived control did not change (Table S6).

H6: The effect of knowledge on intention

In LMMs, knowledge was associated with more positive behavioural intention (β_{kno}=0.14, SE=0.06, $p=0.02$), attitudes (β_{kno}=0.31, SE=0.08, $p<0.01$), perceptions of control (β_{kno}=0.23, SE=0.07, $p<0.01$), perceptions of descriptive norms (β_{kno}=0.09, SE=0.04, $p=0.04$), and perceptions of injunctive norms (β_{kno}=0.32, SE=0.09, $p<0.01$). In imputed data, the effect of knowledge on intention and perceptions of descriptive norms were not significant. Modelling knowledge of each intervention component separately, the only significant correlation was between knowledge about the hotline and perceived injunctive norms (β_{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 (Table 2, Model 1, effect 3).

H7: Peer influences on intention

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 behaviour $= e^{\frac{1.713}{8}}$). This effect did not vary over time or with knowledge of the intervention (effects 5 & 6). There was also a tendency to reduce intention in the second period (i.e., between waves 2 and 3, effect 4), which was not accounted for by other effects, indicating a potential weakening of the intervention's effects over time.

H8: Peer influence mechanisms

Peer intentions and attitudes did not predict changes in perceived norms (Table 2, Models 2 & 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 reduce in the second period (i.e., between waves 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-behaviour dynamics, longitudinal behavioural data collected across an entire village, and an innovative study design, we show how social networks shape the outcomes of an important conservation intervention. Specifically, we show that a social marketing event aiming to reduce wildlife poisoning by encouraging use of a reporting hotline had spill-over 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 two weeks, and information from the intervention spread widely through the village. However, despite lasting changes in some psychological outcomes, such as perceived behavioural control and attitudes, the intervention failed to change behavioural intentions in the long term. Evidence from SAOMs suggests 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, as this was considered an essential precondition for behaviour change. This information flowed relatively well for a small intervention; after six months, the number of residents knowledgeable about the intervention more than tripled. Much of this flow could be predicted by household co-residence 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 behavioural intention (Table 2). Instead, individuals with more positive attitudes towards 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 behaviour (Prentice & Paluck, 2020). Rather than driving behavioural change, communication about the new behaviour may ultimately have reinforced the status quo, pushing residents to conform with existing levels of behaviour. This contradicts evidence from elsewhere that increased communication about a new conservation behaviour tends to increase behavioural change (Green et al., 2019).

Although our models indicated that social influences were occurring, we could not establish the cognitive mechanisms underlying this effect as peer intentions did not appear to drive changes in perceptions of descriptive norms, nor did peer attitudes influence perceptions of injunctive norms (Cialdini et al., 1991). Perhaps individuals are mis-perceiving the attitudes or intentions of their peers because reporting poisoning is both a rare and potentially sensitive behaviour, which makes observation of others' behaviour or communication about the behaviour 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 behavioural 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, which tend to be similar for socially close individuals and which are challenging to discount in observational studies (Shalizi & Thomas, 2011). Alternatively, individuals' norm perceptions may be informed by individuals with whom they didn't 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 behaviour changes to occur (such as information about the hotline), and using appropriate message framings to influence norm perceptions, attitudes, and perceptions of control, our intervention failed to change intentions in the long-term. The countervailing effect of social influence indicates 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 behaviours, 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 behaviour change to occur. To sustain these impacts and create behaviour 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 (Valente, 2012; Centola, 2018). 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, anti-poisoning interventions could be integrated with broader social interventions, such as the Ibis Rice conservation agriculture programme, 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 (Groce *et al.*, 2018; de Lange et al., 2019). Using an innovative network modelling approach (Greenan, 2015; Steglich, Snijders & Pearson, 2010), we interrogated the social influence processes that followed a conservation intervention. Our results highlight the critical importance of social relations in shaping conservation behaviours. In keeping with the theory of complex contagions, we found that information flow occurs more easily than behaviour change, and does not lead straightforwardly to change in intention (Schultz, 2002; Centola, 2018). 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 (Ferraro & Pattanayak, 2006; de Lange et al., 2019).

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Data availability

Data and code to replicate all the analyses described here are available online at: https://github.com/emieldelange/Social-Influence-Information-flow

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Wave	Dates	Before or after intervention	Data Collected	No. of individu completeness of ne
Zero	26/09/17 – 07/10/17	Before	Social network	365 (100%)
One	21/01/19 – 27/01/19	Before	Psychological outcomes	181 (50%)
Two	25/02/19 – 06/03/19	After	Psychological outcomes & knowledge	283 (78%)
Three	10/08/19 – 31/08/19	After	Psychological outcomes, knowledge, & social networks	191 (53%)

Table 1: An overview of data collection for this study. The intervention took place on 13th February 2019

Dependent variable:	**1. Change in Intention**		**2. Perceived descriptive norm**		**3. Perceived Injunctive norm**	
Effect	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
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
Interactions						
5. Social influence x Knowledge	+0.381	0.487	-0.011	0.029	+0.006	0.013
6. Social influence x 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	+0.040	0.040	+0.140	0.068	+0.029	0.031

agriculture						
15. Pesticide use	-0.007	0.047	+0.009	0.069	-	-

Table 2: Summary results from three Stochastic Actor Oriented Models modelling the effect of the social network on 1) intention to report poisoning, 2) perceived descriptive norms, and 3) perceived injunctive norms.

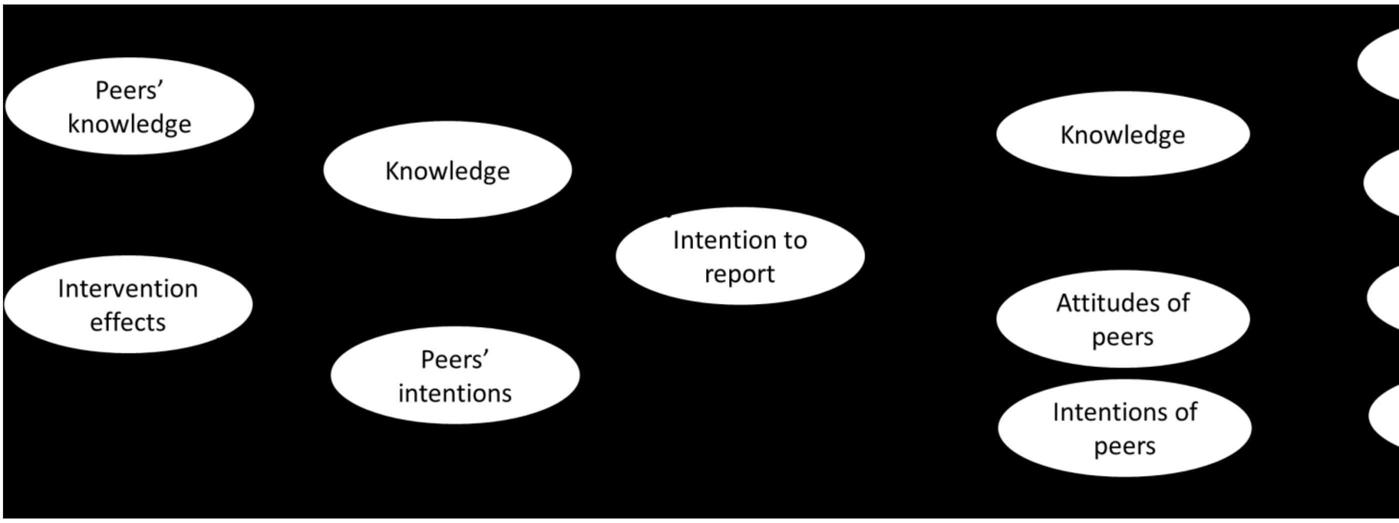

Figure 1: The hypothesised and observed relations between knowledge and variables from the theory of planned behaviour (TPB) throughout the village. The main hypothesised processes are labelled H1 to H8. The data were analysed using a combination of linear mixed effect models and stochastic actor-oriented models (SAOM). Left: Overview of the observed mechanisms of behaviour change in the village. The intervention influenced people's intentions (H2) and increased knowledge about reporting of poisoning (H1). Information flowed through the village (H3, 4) but did not lead to increased intention (H6). Intention changed throughout the social network (H5) through social influences (H7). Right: Further detail on the hypothesised and observed cognitive mechanisms of behaviour change. Dotted arrows indicated hypothesised relationships between variables that were not supported by the data, while the thicker solid arrows represent correlations observed in the data. For the TPB variables, small circles indicate whether the variable changed in the short term (left) and long term (right). Black indicates change, and white indicates no change, relative to the baseline. In turn, attitudes, perceived behavioural control, and perceived injunctive norms also correlated with intention. SAOMs showed a strong effect of peer intention but did not support other social influence mechanisms (H8).

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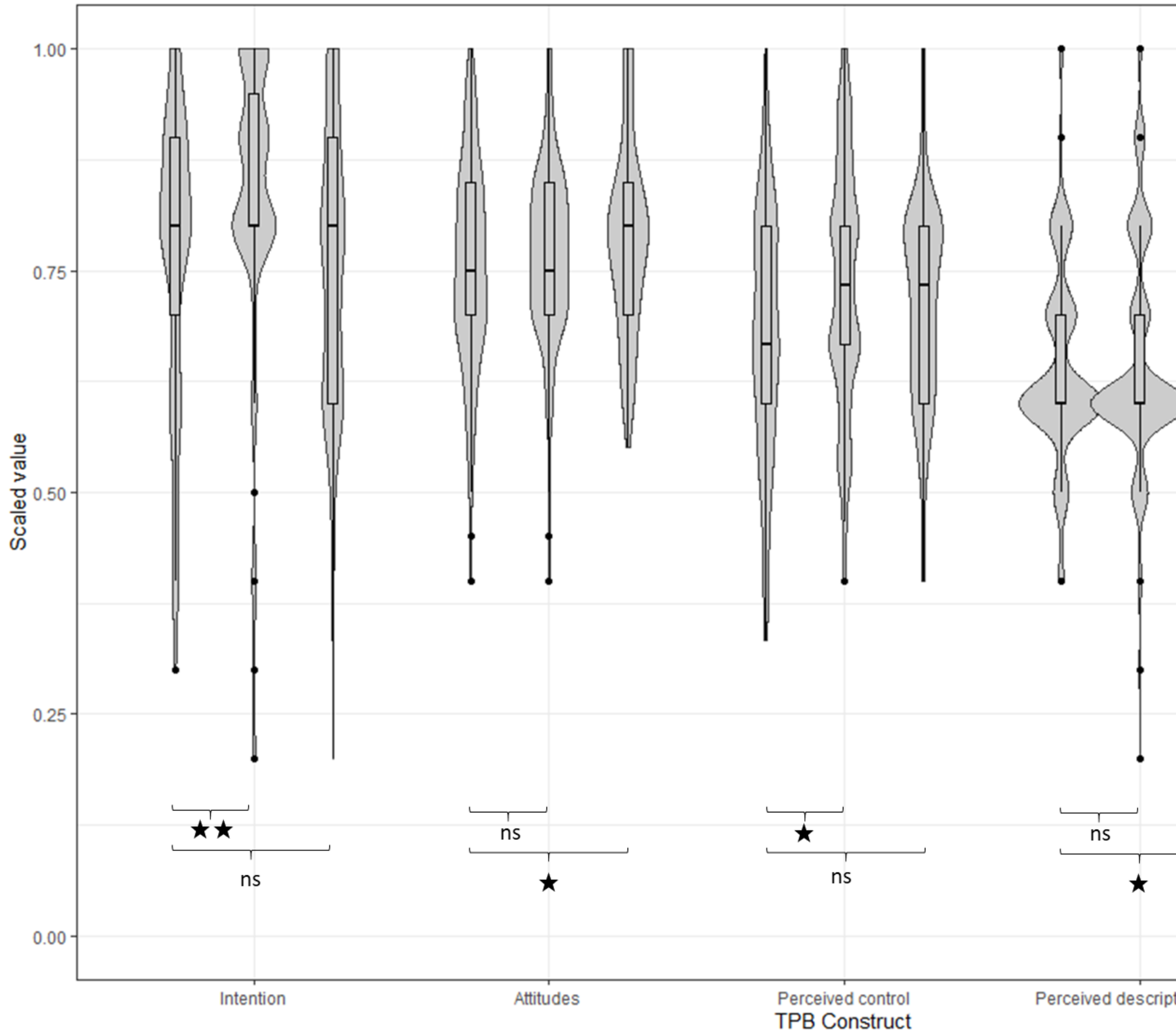

Figure 2: Changes in the measured values for each construct from the Theory of Planned Behaviour. From left to right: intention to report poisoning, attitudes towards reporting, perceived control, perceived descriptive norms, and perceived injunctive norms. Each construct is constructed from a set of questions answered on a five-point Likert scale. The range of values for each construct differs, so they are scaled from 0 to 1 to enable visual comparison. The mean value is shown by a black stripe, the box indicates the standard deviation, and the whiskers represent the 95% confidence intervals. Outliers are shown by dots. Significance levels are shown for the differences between waves, estimated using linear mixed effect models (* p<0.5, ** p<0.1, *** p<0.001, ns: not significant).

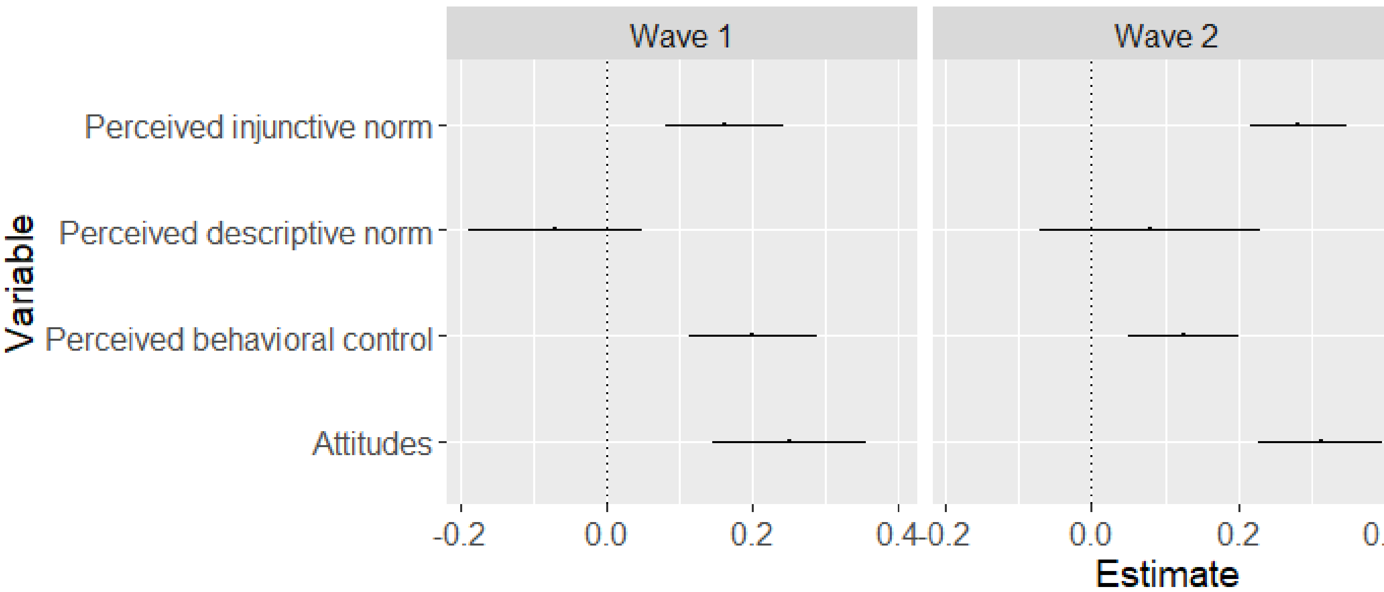

Figure 3: Estimates of the relationships of attitudes, descriptive norms, injunctive norms, and behavioural control with intention to report poisoning. The coefficients were estimated from Generalised Linear Models, using complete case data at each survey wave. Intention is positively correlated with attitudes, perceived injunctive norms, and with perceived behavioural control at all time points, but not with perceived descriptive norms. The relative importance of the perceived injunctive norm increases relative to perceived behavioural control in wave 2. 95% confidence intervals are shown.

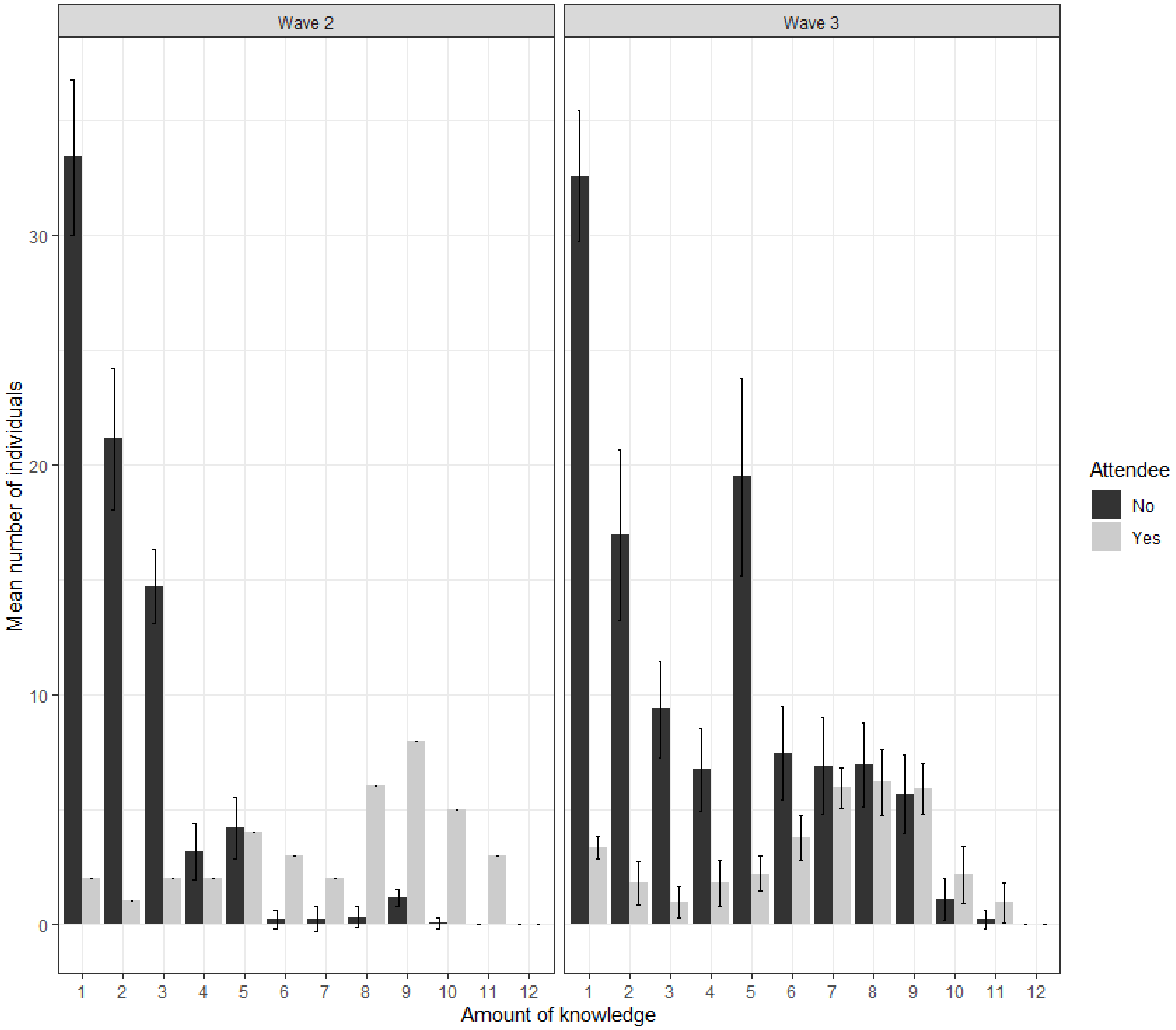

Figure 4: Change over time in knowledge about the intervention. The mean number of individuals with each level of knowledge (measured out of 12), across twenty imputations. Those who participated in the event are shown in grey, while those who did not are in black. Before the intervention, in wave 1, nobody has knowledge because the messages were designed to be unknowable to those not attending the event. Wave 2 (left) was measured two weeks following the intervention, while wave 3 (right) was measured after six months. The standard error bars show the variation between imputations. Individuals without any knowledge are not shown: 248 non-participants (SD=5) and 1 participant (SD=0) in wave 2, and 213 non-participants (SD=8) and 4 participants (SD=1) in wave 3.