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The Acquisition of Perceived Descriptive Norms as Social Category Learning in Social Networks

Yoshihisa Kashima¹,², Samuel Wilson³, Dean Lusher⁴, Leonie J. Pearson²,⁵, & Craig Pearson²,⁵

Brief Abstract: Descriptive norms are norms about what people typically do in a community. People can acquire knowledge about their community’s descriptive norms experientially by observing what others do in their local social network or conceptually by hearing what others say people typically do. People’s personal community engagement and their perceived descriptive norms about community engagement were examined in a survey of a snowball sample of the residents in a rural town in Australia. Using autologistic actor attribute model, they were found to learn about their community’s descriptive norms by observing the behaviours of others in their local social networks.

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Descriptive norms – what people typically do in a certain setting – play a significant role in people’s behavioural decisions. However, little is known about how people acquire descriptive norms in their community. We postulate that acquisition of descriptive norms can be construed as social category learning in social networks, where people learn social information relevant about community descriptive norms from others with whom they are associated through social network ties. We distinguish two routes to norm acquisition: experiential and conceptual. The experiential route suggests people observe the behaviours of their associates in their social networks, and infer what people typically do; the conceptual route suggests people learn about their community from what their associates say people typically do. We used a novel statistical method of autologistic actor attribute models (ALAAM) on survey responses collected by snow ball sampling in a rural city in Australia, and found that people experientially learn descriptive norms about community engagement. Implications of this finding and the limitations of the current study are discussed.

Keywords: Norm Learning, Descriptive Norms, Social Networks, Social Category, Category Learning
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Social norm is one of the central concepts in social psychology. Although Cialdini, Reno, and Kallgren (1990) observed that social norm had a mixed reception two decades ago, there is now growing recognition that it plays a significant role in behavioral prediction and explanation (e.g., Revis & Sheeran, 2003; Smith & Louis, 2009). In particular, one of the most significant predictors of social behaviour is descriptive norm (Cialdini et al., 1990) – what many people do in a given reference group. From health-relevant behaviours such as smoking (Schofield, Pattison, Hill, & Borland, 2001), binge drinking (Johnson & White, 2003), and healthy eating (Louis, Davies, Smith, & Terry, 2007) to environment-relevant behaviours such as littering (Cialdini, Kallgren, & Reno, 1991), recycling (Schultz, 1999; Terry, Hogg, & White, 1999), and energy conservation (Goldstein, Cialdini, & Griskevicius, 2008; Schultz, Nolan, Cialdini, Goldstein, & Griskevicius, 2007), once learned, descriptive norms exert a powerful influence on human behaviours (Manning, 2009, for a meta-analytic review).

This raises a significant question. If descriptive norms exert such a strong influence on behaviour, how are the descriptive norms learned to begin with? To be sure, some descriptive norms are people’s readily observable behaviours, or their outcomes, such as littering or rubbish observed in a specific physical setting such as a parking lot (e.g., Cialdini et al., 1990). The acquisition of a descriptive norm of this sort is perhaps a trivial question. People learn the descriptive norm based on the directly observable characteristics of the setting (i.e., how many pieces of rubbish are there?). However, many others are concerned with highly private behaviours (e.g., extradyadic sex, condom use), so that firsthand direct observations are rarely available (see Revis & Sheeran, 2003). Furthermore, if the reference group of a descriptive norm is a large collective that includes a large number of people, how do they learn the descriptive norm of a community of thousands of people? We suggest that social networks – recurrent patterns of interpersonal interactions among people in a community – play an important role, and report a study that examines potential social network mechanisms for the acquisition of a descriptive norm about community engagement.

Acquisition of Descriptive Norms as Social Category Learning in Social Networks

Our main theoretical contention is that the acquisition of a descriptive norm of a large collective can be construed as the learning of a social category within social networks. This proposition has two main components. First, people learn information about a social category that represents the collective, and this information is used to infer the distribution of the members’ attitudes and behaviours within the collective. Second, information relevant for category learning comes from those with whom people are connected through social network ties. We address them in turn.

Acquisition of descriptive norms as social category learning. Consider a descriptive norm about energy use (e.g., Schultz et al., 2007) as an example. It is the average energy use of a neighbourhood. Consider another descriptive norm about petition signing (e.g., Smith & Louis, 2009). It is the behaviour performed by the majority (i.e., mode) of the relevant group. In other words, a descriptive norm is construed as the central tendency (e.g., mean, mode) of the distribution of a certain attribute within a group. Therefore, the acquisition of a descriptive norm can be thought of as a result of the learning of exemplars of a social category. When information about a group is encountered over time, the information is encoded, and the encoded information is cumulated in a memory system; when this system is accessed by a retrieval cue about the group, the prototypical
representation (in other words, a central tendency of these exemplars) is likely to be generated. In other words, the retrieved prototype is very much like a perceived descriptive norm, namely, what people think most people in a group do (e.g., Kahneman & Miller, 1986; Kashima, Woolcock, & Kashima, 2000; Turner, 1987).

Nevertheless, as Kashima, Woolcock, and Kashima (2000; also see Linville & Fischer, 1993; Park & Hastie, 1987) noted, there are two types of learning about a social category, and therefore of a descriptive norm. One is experiential, where people have direct experience of the exemplars of the category; the other is conceptual, where people learn an abstract verbal summary about the category. So, when a traveller arrives in a town, observes the townsfolk’s behaviours, and learns that most people there do not litter, this involves an experiential learning of the descriptive norm, whereas the traveller learns from a friend that the town is clean and no litter to be seen on the street, this involves a conceptual learning.

The experiential and conceptual routes to the acquisition of descriptive norms imply different cognitive processes. On the one hand, the experiential route implies a direct firsthand experience of exemplars of the social category, and therefore the norm learner needs to learn the psychological attributes of particular individuals of the collective. According to the exemplar theory of category learning (e.g., Kahneman & Miller, 1986; Kashima et al., 2000), when individuals who belong to a collective exhibit certain psychological attributes (e.g., attitude, behaviour), this is encoded as exemplars of the collective and generalized to the social category unless there is a reason not to, and forms the cognitive representation of the collective. For instance, Kashima et al. (2000) showed that group members’ expressed opinions about the current societal treatment of Australian Aborigines systematically influenced the perceived descriptive norm of the group. On the other hand, the conceptual route involves the acquisition of a descriptive norm through a summary description about the collective (e.g., “This town is environmentally conscious”). This type of information is typically socially communicated to the learner of the social category, and involves indirect hearsay, or secondhand information, from the norm learner’s perspective.

**Social category information comes from social networks.** It is often through social network ties that an individual is exposed to social information (Granovetter, 1973), particularly, information about social groups (e.g., Lyons, Clark, Kashima, & Kurz, 2008; see other discussions about social influence in social networks, e.g., Reifman, Watson, & McCourt, 2006; Robins, Pattison, & Elliott, 2001; Visser & Mirabelle, 2003; see for a review, Mason, Conrey, & Smith, 2007). The role of social networks in the formation of descriptive norms was highlighted by Friedkin (2001). He analysed the data from the classic study of the Western Electric’s Bank Wiring Observation Room (Roethlisberger & Dickson, 1939), where a group of workers’ performances was observed. Despite a significant conflict and continuing disagreements within the group, the group was able to sustain a descriptive norm about an appropriate level of productivity. Friedkin showed that it was the result of social influences that were exerted through the social networks among the workers, which enabled them to sustain the descriptive norm about performance.

Further extending Friedkin’s insight, we suggest that the two types of norm acquisition, experiential and conceptual, imply different dynamics about norm formation in social networks. In particular, they differ in the type of social network ties that the norm learner (Ego), who holds a certain
perceived descriptive norm, should have with another person in the community (Alter), who has different types of psychological attributes.

First of all, the conceptual route to descriptive norm acquisition suggests that Ego who has a descriptive norm (e.g., many people in the community perform pro-environmental behaviour) should have a network tie with an Alter who also has the same descriptive norm (i.e., many people in the community perform pro-environmental behaviour). This is because the conceptual route implies that Ego acquires a descriptive norm via an Alter’s communication about his or her perception of the descriptive norm, namely, a summary description of the collective. In network terms, this can be understood as either contagion or homophily. Contagion occurs when an Alter’s attribute is transferred to Ego, just like when the Alter’s contagious disease spreads to Ego. Although contagion has long been discussed in social psychology (e.g., Crandall, 1988; Hatfield, Cacioppo, & Rapson, 1994), recent high-profile results have been interpreted as showing that obesity (Christakis & Fowler, 2007), cessation of smoking (Christakis & Fowler, 2008), happiness (Fowler & Christakis, 2008a) and loneliness (Cacioppo, Fowler, & Christakis, 2009) may all spread through social networks. It is also important to recognize that Ego and the Alter can have the same attribute because they form a relationship because they have similar attitudes and behaviours (e.g., similarity-attraction, Byrne, 1971). This tendency is called homophily (e.g., McPherson, Smith-Lovin, & Cook, 2001). Although it is difficult to separate contagion and homophily (see e.g., Shalizi & Thomas, 2011; also see Cohen-Cole & Fletcher, 2008; Fowler & Christakis, 2008b), it is well established by now that people with similar attributes tend to have a network tie. Likewise, people with a similar perceived descriptive norm may have a network tie.

In contrast, the experiential route to descriptive norm acquisition implies that Ego who holds a perceived descriptive norm about a certain psychological attribute (e.g., many people in the community perform pro-environmental behaviour) should have a network tie with an Alter who has that attribute (i.e., The Alter performs pro-environmental behaviour). This is because it is from the Alter that Ego acquires information about the Alter’s attribute (rather than the Alter’s perceived descriptive norm about the attribute) as exemplar information about the category. Ego then generalizes this perception to the collective as a whole, leading to the inference that the community is pro-environmental. There is some evidence for this mechanism in the social network literature. In a study on a US presidential election, Huckfeldt, Beck, Dalton, and Levine (1995) found that people thought there was greater support for a candidate if they knew someone who supported that candidate. Similarly, Real and Rimal (2007) reported that peer communication (i.e., how often participants talked about drinking alcohol) positively correlated with perceived descriptive norms (i.e., average peer’s drinking behaviour). However, these studies basically reported correlations between Ego’s perceived descriptive norm and Ego’s perception of Alters. This could be simply a reflection of a social inference process – most people in a group have an attribute; an Alter is a member of the group; therefore, the Alter has the attribute. We seek to provide evidence for a relationship between Ego’s perceived norm and the Alter’s actual attribute.

In considering the experiential route to descriptive norms, however, it is important to consider an additional possibility, namely, social projection (e.g., Krueger & Clement, 1996; Robbins & Krueger, 2005). Provided that Ego is a member of the collective to which the descriptive norm pertains, it is possible that Ego may project his or her own attitudes and behaviours to the whole of the collective, inferring that “Most people do what I do.” In fact, there are many, well documented biases in
people’s estimation of the distribution of psychological attributes within a group. They include false consensus (e.g., Ross, Greene, & House, 1977; Marks & Miller, 1987, for a review), false uniqueness (e.g., Suls & Wan, 1987), false polarization (e.g., Robinson, Keltner, Ward, & Ross, 1995), and pluralistic ignorance (e.g., Prentice & Miller, 1983; Miller, Monin, & Prentice, 2000, for a review). These potential biases need to be considered in interpreting people’s perceived descriptive norms.

In sum, people may acquire their perception of a community descriptive norm on the basis of the words and deeds of those others that they are associated in their local social networks. They may learn a descriptive norm – what the majority of the community does – through the conceptual route by hearing what these others say, or through the experiential route by observing what these others do. The two routes to the acquisition of a descriptive norm are not mutually exclusive, however, and they may both occur in parallel. We sought evidence for the operation of these mechanisms in the present study. In addition, we also explored the relationship between people’s personal attribute and their perceived descriptive norm. Their personal attribute may be influenced by their perceived descriptive norm, but their personal attribute may be projected to their community, so as to influence their perception of their community’s descriptive norm. We explored this question as well.

Present Study

Many regional communities in Australia increasingly face social and ecological challenges directly associated with an upheaval being experienced in agriculture (Tonts, 2000). As Smailes (1995) suggested, many of these towns have experienced declining economic activity, rising unemployment, depopulation, and the breakdown of local institutions and social networks. Growing concern about the health of the ecosystems in which these communities are embedded compounds the socio-economic challenges facing these communities. These concerns about ecosystem health are especially pronounced in Australia’s Murray-Darling Basin. For example, the Wentworth Group of Concerned Scientists (2010) argue that the water extraction industries (e.g., irrigated agriculture) that have been developed in the Murray-Darling Basin over the last 100 years have left too little water in the rivers to maintain a healthy river system. As a result, there is a risk that the ecosystems supporting the river system may collapse, undermining the businesses and communities (i.e., the social systems) that depend on it.

Against this background, the main psychological attribute of our interest was community engagement. Although community engagement is often construed in terms of psychological sense of community, largely a construct that taps people’s psychological belongingness to their community (e.g., Sarason, 1974; McMillan & Chavis, 1986), we wished to tap psychological readiness to actively participate in the community activities especially as they relate to the betterment and protection of the township and its natural environment. A similar construct was recently suggested by Nowell and Boyd (2010) as sense of community as responsibility. They reported that their interviewees expressed a “sense of responsibility for the betterment and well-being of the other members.” Although we were unaware of their work at the time of our investigation (our data were collected in early 2010), our measure of community engagement was designed to tap a construct akin to this sense of community as responsibility. Given this focus on community engagement, we surmised that social network processes were likely to play a significant role in the formation of a descriptive norm held in the community.
The present research investigated the process of the acquisition of descriptive norms in a community sample. We used a snowball sampling method to obtain survey responses about their community. As we will describe in greater detail later, this method allowed us to measure the respondents’ social network ties as well as their own personal community engagement and perceived descriptive norms about community engagement. The main objective of the research was to examine whether the experiential or conceptual route was employed for community members’ acquisition of the perceived descriptive norm about community engagement. These two routes are not competing mechanisms, and therefore it is possible that one or the other, or both processes are in operation. The design also allowed us to explore the effects of perceived descriptive norm and social network processes on people’s own community engagement; we report these results as well.

**Methods**

**Participants and Sampling**

The Murray-Darling Basin community chosen was an irrigation-dependent region in the New South Wales’ Riverina. This community was predominately Anglo-Celtic at its inception, attracted Italian and Greek immigrants after the Second World War and has a small indigenous community. According to the Australian Bureau of Statistics (ABS) census data from 1996, 2001, and 2006, the ethnic and demographic profile of this community (predominantly Anglo-Australian) and its population (~11,000) has remained stable for decades. The largest industries in this community are manufacturing, value-added processing, and construction. Consistent with the employment profile of this community, ABS data indicates that 40% of people employed in the community work in jobs associated with low human capital (e.g., labourers and related workers), 30% of people work in jobs associated with moderate human capital (e.g., intermediate clerical, sales and service workers), and 20% work in jobs associated with high human capital (e.g., professionals, managers), while 10% did not provide information about their occupation.

We used a snowball sampling approach (based on Goodman, 1961). We first contacted a seed set (Wave 0; N = 16), and asked each participant to nominate up to five people with the following question:

> Please think of up to 5 people that you know in this town —outside of your own household—with whom you have strong social relationships. These may be people you can talk to about life, family, or community matters, people you may socialize or enjoy time with, people from whom you can gain support for new ideas, or perhaps go to if you face any problems that you need help with.

This method of asking participants to recall contacts results in their strong and frequently-used social ties (Freeman, Romney, & Freeman, 1987). Further, the ties are specifically outside of one’s own household, and so are more likely to be directed towards wider community members. Social community ties were coded as binary and undirected\(^1\).

\(^1\) At the time of writing, autologistic actor attribute models (see later in this section for details) are only implemented for non-directed data, and while there is directionality in snowball sampling, such information was necessarily disregarded.
A researcher then followed up the nominees, and if they agreed to be interviewed, we included them at Wave 1 (N = 49). Following the same procedure, we included additional participants in Wave 2 (N = 39). In the end, participants were 104 adults (36 women, 68 men) with their ages ranging from 18 to 83 years (M = 51.05). Eighty-nine participants identified as Anglo-Australian, eight as Italian-Australian, five as Aboriginal-Australian, and two as Dutch-Australian. In total 375 people were nominated but we could only include in the analysis those people who also completed the survey.

**Interview Items**

Participants self-reported their responses about personal community engagement (or engagement with the socio-ecological system) and also perceived descriptive norm of community engagement. Community engagement was measured by the following two questions: ‘I am always extremely careful to protect this town and its natural environment from any harm’ and ‘I always work energetically to improve this town and its natural environment, to the extent I can’. The perceived descriptive norm about community engagement was derived from the average of responses to the following two questions: ‘The people of this town put a lot of energy into working together—as a community—to improve the town and its natural environment’ and ‘The people of this town are extremely careful to work together—as a community—to protect the town and its natural environment’. All responses were made on a 5-point Likert scale (1= strongly disagree to 5 = strongly agree).

In addition, we measured two classes of variables that we thought should relate to personal community engagement. The first had to do with respondents’ identification with their community itself. Attachment to the community was measured by three items: ‘I feel strongly connected to or attached to the community’; ‘I am strongly committed to the community’; ‘I will continue to live in the community for the foreseeable future’ (5-point Likert scale). A graphical measure of community identification was also used. Eight steps of graphic depictions of two circles were presented, one circle representing the self and the other, the community, with differing degrees of overlap from complete separation (1) to complete overlap (8). Participants were asked to express the degree of overlap between their own personal identity and the community by choosing one. This is based on Schubert and Otten’s (2001) measure of overlap of self-ingroup representations, which was extended from Aron, Aron, & Smollan (1992).

The second class included measures of people’s identification with the natural environment that surrounds their community. One was a single item measure of attachment to the environment: ‘I feel strongly connected or attached to the natural environment’ (5 point Likert scale). The other was a self-environment overlap measure. Like the self-community overlap measure, there were eight pairs of circles with different degrees of overlap from complete separation (1) to complete overlap (8). Participants were asked how they would express the degree of overlap between their own personal identity and the natural environment, and told to select one to indicate their identification with the environment. This was based on Schultz’s (2001) extension of Aron et al.’s measure (1992).

**Autologistic actor attribute models (ALAAM)**

Our analyses employ a variation of a particular class of statistical models for social networks, generally known as exponential random graph models (Frank & Strauss, 1986; Pattison & Wasserman, 1999; G. Robins, Elliott, & Pattison, 2001; G. Robins, Pattison, & Elliott, 2001; Garry
Robins, Pattison, & Wang, 2009; Snijders, Pattison, Robins, & Handcock, 2006; Wasserman & Pattison, 1996). These are called autologistic actor attribute models (ALAAM: Daraganova & Robins, 2013). In short, ERGMs are models for predicting network ties, whereas ALAAMs are models for predicting the attributes of network actors (Lusher, Koskinen, & Robins, 2013). The main difference between standard statistical methods (e.g., logistic or multiple regression) and the ALAAM network approach is the assumption of independence between observations. In classic statistics, observations (in this case, individual attributes) are independent of each other, while in the ALAAM approach the observations (individual attributes) are dependent upon each other by means of dyadic relationships (if they share a tie). Daraganova and Robins (2013) extending the work of Robins et al. (G. L. Robins, Snijders, Wang, Handcock, & Pattison, 2007) developed forms of dependencies between observations (attributes) that emerge by means of a shared tie and could be represented as configurations (see Table 1). Each configuration reflects a particular social process, and the configurations included in our models are presented in Table 1.

More specifically, ALAAMs permit an understanding of how an individual’s psychological attributes may be constrained by his or her position in a social network and the behavior of other actors within that network. ALAAM adopts a special modelling framework that conditions each respondent’s psychological attribute on the respondent’s social connections with others. Due to the complex dependency of psychological attributes of people connected via social network structures (they interact with each other, and this produces dependency among their psychological measures just as a dyadic interaction is bound to produce dependency between the interactants’ psychological attributes), a simple multiple regression or logistic regression analysis of predicting a respondent’s perceived descriptive norm by an Alter with whom he or she is connected does not yield a statistically sound inference of the network effects.

Building on the work of Robins, Pattison and Elliot (2001), Daraganova and Robins (2013) have shown that a general expression for a probability model for attributes $Y$, given the network $X$, can be expressed in the form:

$$
\Pr(Y = y | X = x) = \frac{1}{\kappa(\theta)} \exp\left(\sum_C \theta_C z_C(y, x)\right)
$$

(1)

where $z_C(y, x)$ is a statistic corresponding to a configuration $C$ defined by a combination of attribute, network variables; $\theta_C$ is a parameter corresponding to a configuration $C$; $\kappa(\theta)$ is normalising quantity, which ensures that (1) is a proper probability distribution (that is, it sums to 1). This model aims to describe the distribution of attributes across a network and identify which tie configurations are more likely to be important while taking into consideration other actor-level attributes^2.

Equation 1 describes a probability distribution of vectors on $n$ nodes in a given graph $x$. A specific probability is assigned to each possible vector based on the frequency of various configurations and on the parameter values. As noted by Daraganova and Robins (2013, p. 105), ALAAM predicts “the outcome variable $Y$ while taking the network dependencies between observations into account in a

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^2 We note also that ALAAM can accommodate dyadic covariates, though we have not included these in our analyses, and so have excluded them from equation (1).
principled way that cannot be addressed in the standard logistic regression. It is worth emphasising that when the dependence among attributes via network ties is not assumed the ALAAM is equivalent to standard logistic regression”.

There are three advantages in using the ALAAM framework. First, ALAAM allows us to treat personal community engagement and perceived descriptive norm about community engagement as a statistical regularity determined through the interactions with, and characteristics of, others, while simultaneously recognising some variability in individual behaviours that cannot be modelled. Second, it allows us to develop a range of complex dependence assumptions regarding the social processes and estimate a separate parameter for each possible structural characteristic. The flexibility and generality of the exponential random graph modelling framework allows us to specify an explicit probability model characterising individual outcomes conditional on the endogenous individual characteristics of others and upon network structure, and then assess the contribution of each effect in the model. In the end, the estimation of ALAAM allows us to assess associations between individuals’ responses with other individual-level variables and also social network ties. Third, as we have collected snowball sampled data we require a model that can take this into account in a principled manner, and ALAAM has such capabilities, making it advantageous over other modelling options (Daraganova & Pattison, 2013; P. E. Pattison, Robins, Snijders, & Wang, 2012).

Variables and model specification. The relevant social network information and respondents’ attributes – personal community engagement and perceived descriptive norm of community engagement – were included in the ALAAM analyses. There were two basic types of parameters: First there were structural social influence parameters (which deal only with the impact of network ties on the dependent variable), and the second were actor-attribute parameters (which deal with how the attributes of ego or alter impact on the dependent variable). Specific details of both types of parameters are in Table 1. The structural social influence effects represent the propensity for an actor to have the target attribute based purely on network structures (and not individual attributes). The attribute density effect represents the occurrence of actors with the target attribute in the network. It acts as a baseline comparison by which to interpret the other effects. Actor activity and star-2 effects both reflect the propensity of an actor with the target attribute (e.g., perceived descriptive norm of high community engagement) to be tied to others; activity represents the propensity for Ego with the attribute to have a network tie with an Alter, whereas star-2 represents the propensity for Ego with the attribute to have more than one network tie with Alters. Finally, contagion represents the propensity for an actor with the target attribute to be connected to another with the target attribute – and therefore is a measure of diffusion of the target attribute via network ties.

These purely structural social influence effects act primarily as controls in the current analyses for the critical effects of our interest, which are called actor attribute effects. One such actor attribute effect is the ego attribute effect, which indicates the propensity for the Ego with the target attribute to personally have a certain level of a separate attribute (either high amounts for a positive effect; or low amounts for a negative effect). The alter attribute effect indicates the propensity of Ego with the target attribute to be connected to an Alter with high (positive effect) or low (negative effect) levels of continuous attribute.
Results

Preliminary analyses. All the measures with multiple items had acceptable levels of reliability (alpha > .75; Table 2). Correlations between the key variables were computed (Table 2). Personal community engagement correlated with both identification with community and identification with the natural environment significantly. Perceived descriptive norm of community engagement correlated only with identification with community, but not with identification with the environment, suggesting that personal engagement and perceived descriptive norm are distinguishable constructs although they are significantly, but only moderately, correlated with each other. As expected, personal community engagement was predicted, \( R^2 = .36, F(2,102) = 28.49, p. < .01 \), by both identifications with the community (\( \beta_{\text{com}} = .38, t(102) = 4.04, p. < .01 \)) and identification with the environment (\( \beta_{\text{env}} = .30, t(102) = 3.12, p. < .01 \)). The addition of the graphical measures of identifications did not improve prediction (\( R^2 \) change = .00, \( F \) change = .15, n.s.). In contrast, perceived descriptive norm was predicted only by community identification (\( R^2 = .07, F(2,102) = 3.83, p. = .025 \); \( \beta_{\text{com}} = .29, t(102) = 2.52, p. < .05 \); \( \beta_{\text{env}} = -.05, t(102) = -0.42, \text{n.s.} \)). Again, the addition of the graphical measures did not improve prediction (\( R^2 \) change = .05, \( F \) change = 2.52, n.s.). The partial correlation between personal community engagement and perceived descriptive norm was .20 (p. < .05), while controlling for the identifications with the community and the environment. This suggests that there is likely to be both social projection and normative influence.

Experiential and conceptual routes to norm acquisition: ALAAM analyses. In order to examine the nexus of social networks and psychological attributes (i.e., personal community engagement and perceived descriptive norm of community engagement), we fitted autologistic actor attribute models (ALAAM) using iPNet, a social influence-type version of PNet program (P. Wang, G. L. Robins, & P. E. Pattison, 2009). Parameter estimates for the models converged, indicating stable parameter estimates, and goodness of fit t-ratios were less than 0.1 for fitted effects and less than 1 for all unfitted effects, indicating the model is a good fit for the data. We examine two models – one with the target attribute of perceived descriptive norm of high community engagement and the other with the target attribute of Ego’s personal community engagement.

In each model, the target variable was a dichotomized version of the continuous attribute. Dichotomization is required because present implementations of ALAAM only enable analyses of binary target variables. Predictor actor attributes were included as continuous variables. For example, when predicting perceived descriptive norm of community engagement from Ego’s personal community engagement and the Alter’s personal community engagement, the perceived descriptive norm was binary and personal community engagements were continuous. To binarize variables, we examined the joint distribution of responses to the two relevant items of personal community engagement to select those who agreed that they were engaged with their community. Only 14% agreed strongly with both items, 20% agreed with one and strongly agreed with the other, and 35% agreed with both. If we select those who agreed or strongly agreed with both, we end up selecting 69% as engaged; this seemed rather over inclusive. However, if we select only those who agreed strongly with both, we end up with only 14% as engaged; this seemed over exclusive. In the end, we chose the middle option, and counted as 1 (= has target attribute) those who agreed or strongly agreed with both of the two relevant items while at least agreeing strongly with one of...
them, and 0 otherwise (= does not have target attribute). This ended with 34% as personally engaged with community. To be consistent, we followed the same rule to binarize the perceived descriptive norm.

Pattison et al. (2012) proposed conditional maximum likelihood estimation of exponential random graph models for partial network data obtained from multi-wave snowball sampling, which has been implemented in a social influence-type version of the PNet software (Wang, G. Robins, & P. Pattison, 2009). In essence, a snowball network sampling approach using ALAAM means that it is possible to make principled inferences about a population without having to interview the whole network (i.e. all people within the community), and do so while still taking into account the complexity and interdependency of relational, social network data. A parameter estimate that is more than double its standard error in absolute value is said to be significant. We note that the model is for the prediction of actor-level characteristics, given other attributes and network effects. In Figure 1, we see three waves of data collection, beginning in Wave 0 (circles), moving into Wave 1 (squares), and then to Wave 2 (triangles). We note that the conditional estimation procedure relies upon the waves only being connected sequentially, and so we note that Wave 0 is only connected to Wave 2 via Wave 1 – there are no direct ties between Wave 0 and Wave 2. The conditional estimation procedure implies that modelling is done on Waves 0 and 1, conditioning on Wave 2. That is, we are predicting the propensity for actors to have an attribute in Waves 0 and 1, keeping the network ties fixed and the attributes of others in Wave 2 fixed. We fix the nodes in Wave 2 because we do not have information about their network nominations included in the analysis, and as such we may underestimate the effects of network ties on target behaviours. By fixing Wave 2 nodes, the target attributes of such actors are made exogenous to the model and therefore are not predicted, but importantly are not excluded altogether.

When predicting Ego’s perceived descriptive norm of community engagement, we included the structural and actor-attribute effects described earlier (Table 3). The contagion effect captures the effect of the Alter’s perceived descriptive norm on Ego’s perceived descriptive norm; this captures the effect predicated by the conceptual route to norm acquisition as indicated in Table 3. The Alter attribute effect – the Alter’s community engagement – reflects the experiential route to norm acquisition. Consistent with the experiential route, there was a significant and positive effect of Alter community engagement on Ego’s perceived descriptive norm. However, there was no evidence for the conceptual route to norm acquisition. The Alter’s perceived descriptive norm did not predict Ego’s perceived descriptive norm. In addition, there was an effect of Ego’s personal community engagement on Ego’s perceived descriptive norm, suggesting that Ego’s personal tendency was projected to the ingroup (e.g., Robbins & Krueger, 2005).

In addition, a similar model was fitted with Ego’s personal community engagement as the target attribute and Ego’s perceived descriptive norm as well as the Alter’s perceived descriptive norm and personal community engagement (contagion effect in Table 4) as predictors. The only significant effect was found for Alter’s perceived descriptive norm, and it was negative, suggesting that people tended to be engaged if their Alters think their community is disengaged (Table 4). In other words, Ego’s community engagement may be a kind of activism, in which he or she becomes engaged in order to compensate for a perceived lack of community engagement by others. Finally, it is intriguing to note that there was no indication of attitude contagion – the Alter’s personal community engagement influencing Ego’s personal community engagement.
Discussion

Community members seem to acquire their community’s descriptive norm about community engagement through the experiential route, but not through the conceptual route. They learn what people typically do by observing what their associates do – if their associates are personally engaged in the maintenance and transformation of their community, they tend to think the community is engaged as a whole. Our exploration of social determinants of personal community engagement revealed that those who had ties with others who think their community is disengaged tended to be personally engaged with community. It appears to suggest that personal community engagement too is a result of social influence albeit a somewhat more complex one – people around you tell you the community is disengaged, and you become more motivated to be engaged with the community presumably to compensate for the perceived lack of engagement in the community. It is more akin to activism than conformity. This is a novel insight into community engagement that deserves further investigation.

It is important to note that these theoretical insights was gained from the use of the novel statistical method of social network analyses, autologistic actor attribute models (ALAAM), situated in the family of exponential random graph models. This method enabled us to take into consideration the complex dependency that exists in socially networked respondents’ responses, and discern subtle effects of social influences exerted through the social networks. Given that the present data were cross-sectional, many of the questions about causality could not be answered, and yet this modelling exercise enables us to make a somewhat stronger inference about the correlation between people’s personal engagement and perceived descriptive norm using the conventional analytic method. That is, if people think their community is engaged, they too appear to be personally engaged. As we noted earlier, this could be due to the effect of perceived descriptive norm on personal engagement, or the effect of social projection – thinking one’s community is just like oneself. The ALAAM modelling of personal engagement, however, yielded no evidence for the effect of descriptive norm on personal engagement, implying that this correlation is more likely due to social projection in our study. Still, this issue requires further investigation with a longitudinal research design.

That descriptive norms of community engagement are learned experientially has intriguing implications for the psychological mechanisms involved in the conformity to the descriptive norms. First, people are likely to have acquired exemplars of community engagement, and the models of social category learning (e.g., Kahneman & Miller, 1986; Kashima et al., 2000) suggest that the prototypical representation (a central tendency of these exemplars) is likely to be generated when the memory system is accessed by an appropriate cue. This prototypical community member presumably informs people of the prototypical practices that people in the community engage in. That is, it informs people of what to do by increasing the accessibility of this prototypical practice automatically (Sechrist & Stangor, 2001). Then, people are likely to conform to the descriptive norm relatively automatically (Jacobson, Mortensen, & Cialdini, 2010).

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3 At the time of writing, longitudinal statistical models of the ALAAM/ERGM variety for snowball sampling are yet to be implemented.
In addition, our results suggest that other people’s perceptions of descriptive norms can have a somewhat paradoxical effect – if these others say the community is not very engaged, people may become more engaged as if to compensate for the community’s lack of engagement. In the context of the community in which the present study was conducted, those who are personally engaged and yet say most people in the community are not may be an important motivator of the community engagement. Our results imply that those who are associated with this type of people would develop a descriptive norm of community engagement, and at the same time become personally engaged. This kind of social dynamics seems to us to warrant further investigation.

It is also interesting that there was little evidence for contagion in the present sample despite the well documented cases of contagion reviewed earlier in the paper. Recall that, for Ego’s perceived descriptive norm of community engagement, Alter’s perceived descriptive norm was not a significant predictor; likewise, for Ego’s personal community engagement, Alter’s personal community engagement was not a significant predictor. One possible interpretation is that many cases of contagion may in fact be mediated by descriptive norms. So, when an Alter exhibits a certain attitude or behaviour, this may not be simply imitated, but may be taken as an exemplar for the community’s descriptive norm, which in turn may influence Ego’s attitudes and behaviour. A result may look like contagion, but in fact it may be a social influence via descriptive norm. This observation highlights the fact that we know little about the psychological mechanisms involved in contagion, and this issue needs much further examination (see Friedkin’s 2010, recent theoretical investigation on this point).

The present study focused on the acquisition of descriptive norms of community engagement. However, it is important to investigate descriptive norms involving other attitudes and behaviours in developing a theory about descriptive norm acquisition. In so doing, several considerations are likely to be important. First, a referent group for a descriptive norm is likely to depend on a specific attitude and behaviour that the norm is concerned with. For community engagement involving the town and its surrounding environment, it is the community as a whole. For other behaviours such as binge drinking, it is likely to be a person’s peer group. Even for descriptive norms about community engagement, the current status of the community may make a large difference. The current community is a stable community with enduring social networks that have lasted for a long time. In a community that is in transition, the pattern of descriptive norm acquisition may differ greatly.

Finally, the present study did not touch on the other type of social norm that focus theory (Cialdini et al., 1991) postulates – injunctive norms that inform people of what attitudes and behaviours are approved or disapproved by others. The current reasoning suggests that both experiential and conceptual routes to injunctive norm acquisition are also possible. Ego may learn his or her ingroup approves or disapproves of a given attitude or behaviour because an Alter approves or disapproves of it (i.e., experiential route) or because an Alter says that most people in their ingroup approve or disapprove of it (i.e., conceptual route). These issues await further investigation.
References


Author Note

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### TABLE 1: Parameters used in autologistic actor attribute models

- **Denotes actors with attribute Y**
- **Denotes actors with or without attribute**

<table>
<thead>
<tr>
<th>Effect</th>
<th>Configuration</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Structural social influence effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Attribute density</td>
<td>●</td>
</tr>
<tr>
<td>2</td>
<td>Activity</td>
<td>● ○</td>
</tr>
<tr>
<td>3</td>
<td>Star-2</td>
<td>● ○ ○</td>
</tr>
<tr>
<td>4</td>
<td>Contagion</td>
<td>● ● ●</td>
</tr>
<tr>
<td><strong>Actor-attribute effects</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Ego attribute</td>
<td>●</td>
</tr>
<tr>
<td>6</td>
<td>Alter attribute</td>
<td>● ○ ○</td>
</tr>
</tbody>
</table>
Table 2: Correlations between the measures

<table>
<thead>
<tr>
<th>Measure</th>
<th>Mean (SD)</th>
<th>1 (CE)</th>
<th>2 (N_CE)</th>
<th>3 (Id_C)</th>
<th>4 (At_C)</th>
<th>5 (Id_E)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Community engagement (CE)</td>
<td>4.0 (0.7)</td>
<td>(.89)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Descriptive norm of community engagement (N_CE)</td>
<td>4.1 (0.8)</td>
<td>.29**</td>
<td>(.75)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Identity-community overlap (Id_C)</td>
<td>5.2 (1.4)</td>
<td>.38**</td>
<td>.28**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Attachment to the community (At_C)</td>
<td>4.2 (0.7)</td>
<td>.55**</td>
<td>.26**</td>
<td>.60**</td>
<td>(.75)</td>
<td></td>
</tr>
<tr>
<td>5. Identity-environment overlap (Id_E)</td>
<td>5.1 (1.3)</td>
<td>.23*</td>
<td>-.03</td>
<td>.33**</td>
<td>.28**</td>
<td></td>
</tr>
<tr>
<td>6. Attachment to the environment (At_E)</td>
<td>3.8 (0.8)</td>
<td>.51**</td>
<td>.11</td>
<td>.44**</td>
<td>.55**</td>
<td>.50**</td>
</tr>
</tbody>
</table>

Notes: Reliabilities of measures in parentheses along the diagonal. * p < 0.05, ** p < 0.01 (2-tailed).
Table 3: Parameter estimates of the autologistic actor attribute models (ALAAM) for perceived descriptive norm of community engagement

<table>
<thead>
<tr>
<th>Effect Types</th>
<th>Predictors</th>
<th>Coefficient (SE)</th>
<th>Experiential</th>
<th>Conceptual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structural effects</td>
<td>Attribute-Density</td>
<td>-9.113 (2.917) *</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Activity</td>
<td>-1.280 (1.286)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Star2</td>
<td>-0.354 (0.199)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Contagion</td>
<td>-0.575 (0.406)</td>
<td></td>
<td>√</td>
</tr>
<tr>
<td>Actor-attribute</td>
<td>Ego community engagement</td>
<td>1.680 (0.558) *</td>
<td></td>
<td></td>
</tr>
<tr>
<td>effects</td>
<td>Alter community engagement</td>
<td>0.656 (0.305) *</td>
<td></td>
<td>√</td>
</tr>
</tbody>
</table>

Note: * indicates a significant effect at p. = .05
Table 4: Parameter estimates of the autologistic actor attribute models (ALAAM) for personal community engagement

<table>
<thead>
<tr>
<th>Effect Types</th>
<th>Predictors</th>
<th>Coefficient (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Structural effects</td>
<td>Attribute-Density</td>
<td>-1.220 (1.722)</td>
</tr>
<tr>
<td></td>
<td>Activity</td>
<td>1.398 (0.934)</td>
</tr>
<tr>
<td></td>
<td>Star2</td>
<td>0.140 (0.175)</td>
</tr>
<tr>
<td></td>
<td>Contagion</td>
<td>-0.081 (0.393)</td>
</tr>
<tr>
<td>Actor-attribute effects</td>
<td>Ego perceived descriptive norm</td>
<td>0.438 (0.348)</td>
</tr>
<tr>
<td></td>
<td>Alter perceived descriptive norm</td>
<td>-0.464 (0.189) *</td>
</tr>
</tbody>
</table>

Note: * indicates a significant effect at p. = .05
Figure 1: Waves and Zones for social network sampling (n=105104)