Interactions Matter: Modelling Everyday Pro-environmental Norm Transmission and Diffusion in Workplace Networks

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Abstract This chapter demonstrates an approach to the agent-based modelling of norm transmission using decision trees learned from questionnaire data. We explore the implications of adding norm dynamics implied in static questionnaire data and the influence social network topology has on the outcome. We find that parameters determining network topology influence the outcome in both hierarchical and co-worker networks in a simulated workplace. As an exercise in empirical agent-based modelling, this work highlights the importance of gathering data on interactions in field studies.

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1 Introduction

The LOCAW (Low Carbon at Work: Modelling Agents and Organisations to achieve Transition to a Low Carbon Europe)[1] project concerned everyday pro-environmental behaviours in the workplace and their relationship with such activities at home. It focused on three areas of pro-environmental behaviour: waste management, energy consumption and transport. There were six case studies in locations throughout Europe: two in heavy industry, two service companies, a university and a municipality. Agent-based modelling was used in the four case studies not associated with heavy industry to simulate scenarios from back-casting workshops.

Everyday behaviour has been a focus of social science research since the early 1920s (e.g. [1]), and interest in it has been growing rapidly since the 1980s following the work of researchers such as Lefebvre [2] and de Certeau [3]. However, social and (physical) environmental drivers of behaviour are also important in facilitating the insertion of environmental awareness into the everyday—a domain more often associated with habit. In seeking to break the environmentally destructive aspects of habituated lifestyles without draconian regulation, there is an increasing focus on working with communities and engaging social norms. Socially cohesive communities have been found to be more supportive of pro-environmental behaviour [4, 5], and norms have been shown to have a role in predicting some pro-environmental behaviours, such as recycling [6] and household energy use [7].

Agent-based modelling of norms in the context of social control are reviewed by Hollander and Wu [8], who cite Verhagen [9] as couching social control in terms of achieving goals at the social level whilst allowing individual freedom, and Therborn [10] as arguing that social norms are a key tool in addressing the challenge of the social control problem in multi-agent systems. Though they state that normative architectures in agent-based systems have traditionally used Belief-Desire-Intention (BDI [11]) models of decision-making, there has also been a great deal of work on norms using more stylised models, often strongly influenced by game theory. The work of Axelrod [12] has been particularly influential in this area. Elsenbroich and Gilbert [13] provide a comprehensive review of approaches to the simulation of social norms in agent-based models, observing five categories thereof (p. 187), each with potentially different senses of what a norm is:

1. Environmental models, in which an environment contains resources and norms are represented in terms of property rights; the benefits of social norms are assessed by comparing outcomes in models using different decision-making algorithms (p. 90). The environment may also be used as a medium of agent interaction (stigmergy), rather than having the agents interact with each other directly (p. 92).

[1] http://www.locaw-fp7.com/.

2. Game theory models include the work of Axelrod [12], where norms are used as part of the decision-making model of the agents to encourage co-operation in social dilemmas, particularly the prisoner's dilemma.
3. Diffusion models. These are simple imitation models, where norms diffuse through a social network (or space) by agents copying what other agents are doing. The implementation of the imitation typically involves a relatively trivial equation weighting the individual agent's preferences against the behaviours of the other agents it can observe.
4. Social influence and learning models build on diffusion models by adding more deliberation on the part of the agent about whether or not a behaviour is adopted. Elsenbroich and Gilbert [13, pp. 116–120] give opinion dynamics and Schelling's [14] (and Sakoda's [15]) models of segregation as examples of this class, both of which could arguably be in the class of diffusion models, though they point out [13, p. 130] that there is a blurred boundary between diffusion models and social influence models.
5. Cognitive models of norms. These use richer cognitive architectures (such as BDI) from the (distributed) artificial intelligence and multi-agent systems literatures to represent reasoning about norms.

Although Hollander and Wu's [8] norm life cycle model is based on empirical results and theory, there has, interestingly, been relatively little work on the empirical agent-based modelling of norms, as the lack of a relevant category in Elsenbroich and Gilbert [13] suggests. The work presented here attempts to contribute to this area using agents with decision algorithms that include norm transmission (an area Hollander and Wu [8, para. 3.9] note is lacking in agent-based modelling literature), use local injunctive and descriptive norms, and have been configured using questionnaire data.

A growing interest in empirical agent-based modelling [16, 17] means there is a demand for methods to calibrate algorithms in such models from field data. For now, researchers are using standard tools in social science for this purpose: Smajgl et al. [17, p. 838] mention participant observation, surveys, interviews, census data, field experiments and role-playing games among others. Role-playing games are central to the maturing Companion Modelling approach [18] of the so-called 'French School' of agent-based modelling [19]. However, since empirical agent-based modelling typically involves interdisciplinary collaboration of social and computer scientists, we argue that there is a need to build on and develop other tools in social science, and in particular, those that focus on gathering evidence about interactions.

This chapter is concerned with the empirical agent-based modelling of norm transmission as a driver of pro-environmental behavioural change. We fit decision trees to questionnaire data that predict respondents' reported behaviour based on their answers to other questions on individual and normative drivers of pro-environmental behaviour. The questionnaire included questions on norm transmission (how likely the respondent is to tell their colleagues to behave more pro-environmentally), which, together with the questions on normative drivers of behaviour, creates an implied dynamic. The agent-based model simulates that dynamic, and we are interested in the effect the workplace social network has on the effect of the dynamic on the predicted behaviours of the agents. The workplace social network is interesting because interactions are mediated through formal hierarchical relationships and less formal co-worker relationships. Our hypothesis is that parameters affecting the topologies of these interactions affect the predicted behaviours of the agents, where these are affected by norms.

In what follows, we describe the questionnaire, how the responses to it were interpreted into an agent-based model, and experiments with the model exploring network topology parameters. We find that these significantly affect the results of the model, and conclude that empirical agent-based modelling studies (and indeed other empirical work in the social sciences) would benefit from a greater focus on development and adoption of methods for gathering social network data.

2 Method

2.1 Questionnaire Survey

The questionnaire survey included a series of questions about respondents' demographic and psychological characteristics, four questions on norm transmission, followed by several questions on everyday pro-environmental behaviour. The demographic questions included sex, age, education and level in the organisation (top manager, management, supervisory or organisational role). The psychological questions covered various areas, including values [20]. Data on biospheric, egoistic, altruistic and hedonic values were collected using a scale in which -1 represents 'opposed to my values', 0 stands for 'irrelevant' and 1–7 signifies an increasing degree of importance. Other psychological questions included efficacy, worldviews, norms and identity [21, 22]. The questions on norms were most relevant for the purposes of this article.

The norms questions were divided along two dimensions: descriptive versus injunctive norms, and local versus general norms. Local norms are concerned with norms in the workplace for the purposes of LOCAW, whilst general norms cover the respondents' neighbours, city and nation. Local norms are of primary interest for the research in this chapter, and reference to norms henceforth will be to the questions on local rather than general norms.

Descriptive norms focus on people's perceptions of what others are doing, with questions taking the form, "Most of my *colleagues* act pro-environmentally at work," with *colleagues* being replaced by four workplace relationships: subordinates, co-workers, supervisors, and members of the management team (These last two were grouped together, as there was little difference in their interpretation by respondents). Descriptive norms are what would be represented in the diffusion models in Elsenbroich and Gilbert's [13] classification above.

By contrast, injunctive norms pertain to the respondent's perception of what others think they should do, with questions taking the form, "Most of my *colleagues* think I should act pro-environmentally at work." Responses to both descriptive and injunctive norms questions were recorded using Likert scales from 1 (totally disagree) to 7 (totally agree). Hollander and Wu [8] refer to descriptive and injunctive norms as "passive" and "active" transmission respectively (para. 38), but the terms "descriptive" and "injunctive" are applied by Cialdini et al. [23] to contrast norms of what "is" and what "ought" to be.

Knowing what your colleagues think you should do requires them to communicate it to you. Norm transmission questions were added to the questionnaire at the request of the modelling team. Norm transmission in this context may be seen itself as a 'meta' pro-environmental behaviour insofar as it is effective in encouraging colleagues to behave more pro-environmentally. Agent-based modelling is generally held to be suited to contexts in which heterogeneity of and interactions among agents are of importance in determining macro-level outcomes [24]. Although some data on interactions were covered by the section on norms, these questions treat the respondent as a passive observer of their (social) environment; without data on norm transmission, there would have been no empirical basis on which to model agents taking actions to encourage others to behave more pro-environmentally.

Four questions on norm transmission were asked, each taking the form: "How often do you encourage [your *colleagues*] to act pro-environmentally at work?" These and other behaviours questions typically pertain to the respondent's perceived frequency with which they carry out certain everyday environmentally relevant behaviours. Questions not pertaining to norm transmission covered three areas (transport, energy use and waste) in two domains (workplace and at home), but we focus on the workplace in this chapter. The questions used with the model described here were answered using Likert scales from 1 (never) to 7 (always).

2.2 Decision Tree Learning

The demographic and psychological characteristics questions were used as the basis for explanatory variables for decision-tree learning; the everyday behaviour questions (including norm transmission) were treated as response variables. The process by which the decision trees were constructed is described in an accompanying chapter to this book [25], which compares various approaches to pre-processing the data before building the trees. Of the methods described therein, we have adopted here the CFS-MDL-DT approach without values clustering. CFS is Correlation-based Feature Selection [26], which is used to determine which explanatory variables should be sent to the decision-tree learning algorithm; MDL is Multi-interval Discretisation [27]; DT is the C4.5 decision tree algorithm [28]. Although Sánchez-Maroño et al. [25] point out that using values clusters creates different types of agent who behave in different ways, the main aim of this chapter is to see how social network characteristics affect the behaviour of the model. Heterogeneity of agents in this model is determined by their attributes and how these affect the route taken through the decision trees.

The model features trees for four everyday pro-environmental behaviours, and three norm transmissions (to subordinates (NT.1), co-workers (NT.2) and supervisors (NT.3)). The four behaviours are:

- BW.6: When you commute or drive for work purposes, how often do you drive in an energy efficient way (looking ahead and anticipating on traffic and brake and accelerate quietly and change to a higher gear as soon as possible)?
- BW.17: During the year when you are at work, how often do you turn on the heating at your workspace?
- BW.19: During the year when you are at work, how often do you turn on the air-conditioning at your workspace?
- BW.22: How often do you separate your plastic from the regular garbage at work?

These behaviours cover the three areas of behaviour with which LOCAW was concerned (transport, energy and waste), but were primarily chosen for the variety of injunctive and descriptive norms forming the conditional tests at branches in their trees. BW.6 is unaffected by descriptive or injunctive norms; BW.17 is affected by descriptive norms from all kinds of workplace relationship; BW.19 only by descriptive norms from supervisors; and BW.22 injunctive norms from co-workers and descriptive norms from subordinates.

The three norm transmission behaviours are also affected by injunctive and descriptive norms according to the decision trees. Norm transmission to subordinates is affected by descriptive norms from subordinates; norm transmission to co-workers by injunctive norms from subordinates; and norm transmission to supervisors by injunctive and descriptive norms from supervisors.

Figure 1 shows the decision tree for BW.6 and Fig. 2 the corresponding implementation as NetLogo code. The `get-value-of` procedure is described in the submodels section of the ODD in Sect. 2.3, and the source code is in the Appendix to this chapter.

The data used apply to the 'all-country' case study in [25], which amalgamates results from questionnaires sent to the Italian, Romanian and Spanish case studies.

2.3 Model Design

Decision trees for selected pro-environmental behaviours (including all norm transmission behaviours) in the questionnaire were implemented in a NetLogo model WERC-M Q (Worker-Environment Reinforcement Choice Model: Questionnaire). The process of adding dynamics to a static questionnaire involved (a) adding a social network to the agents; (b) interpreting the questions on local norms and norm transmission included in the questionnaire, where these appeared in the explanatory variables of the decision tree:

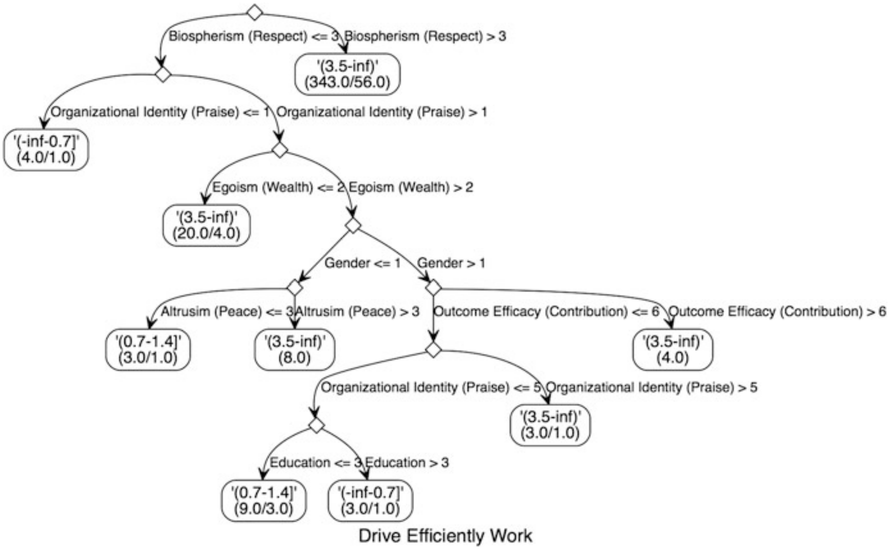

Fig. 1 An example decision tree for driving efficiently when commuting and/or driving on business (BW.6). Decision nodes are represented as *diamonds*, with the branches labelled according to the condition for following them. Leaf nodes show the range of responses from discretisation in quotes

```
to-report dt-drive-efficiently
report ifelse-value (get-value-of "VB.1" "BW.6" <= 3) [
  ifelse-value (get-value-of "IWO.3" "BW.6" <= 1) [0 + random-float 0.7] [
    ifelse-value (get-value-of "VE.2" "BW.6" <= 2) [3.5 + random-float 3.5] [
      ifelse-value (get-value-of "Q1" "BW.6" <= 1) [
        ifelse-value (get-value-of "VA.2" "BW.6" <= 3) [0.7 + random-float 0.7] [3.5 + random-float 3.5]
      ]
      [
        ifelse-value (get-value-of "OE.1" "BW.6" <= 6) [
          ifelse-value (get-value-of "IWO.3" "BW.6" <= 5) [
            ifelse-value (get-value-of "Q3" "BW.6" <= 3) [0.7 + random-float 0.7] [0 + random-float 0.7]
          ]
          [3.5 + random-float 3.5]
        ]
        [3.5 + random-float 3.5]
      ]
    ]
  ]
]
[3.5 + random-float 3.5]
end
```

Fig. 2 Netlogo code corresponding to the implementation of the decision tree in Fig. 1

- For descriptive norms, the response on the questionnaire (to "most of my *colleagues* act pro-environmentally at work") was replaced with an observation based on the agent's immediate neighbours in their workplace social network according to the appropriate workplace relationship. Specifically, the agent looked at the mean response of their subordinates/co-workers/supervisor to the question on the behaviour.

- For injunctive norms, the response on the questionnaire ("most of my *colleagues* think I should act pro-environmentally at work") was replaced with the mean norm transmission of the appropriate workplace relationships.

WERC-M Q is described using Grimm et al.'s [29, 30] ODD protocol below.

2.3.1 Purpose

The purpose of the model is to predict agents' responses to questions about everyday pro-environmental behaviour and norm transmission in the LOCAW questionnaire when the implied dynamics of norm transmission are taken into consideration.

2.3.2 Entities, State Variables and Scales

The entities in the model are the worker agents, each of which has state variables corresponding to the explanatory variables as constant determinants of behaviour. Agents also have dynamic state variables corresponding to each of the norm transmission and selected everyday pro-environmental behaviours. For each of these dynamic state variables, there is a state variable containing the initial value recorded. These variables are all stored in a hash table from variable name to value under the attribute named `data`. Agents also have a `level` attribute, which is their level in the artificial institution the model creates (1 being the most senior level).

Agents are connected in a social network comprising two parts: a hierarchical organisation network, which is a directed graph with each link going from supervisor to subordinate (referred to in the model as a `manager` link), and an informal co-worker network, which is an undirected graph, each link of which represents a mutual co-worker relationship, and is referred to in the model as a `co-worker` link.

2.3.3 Process Overview and Scheduling

Two processes operate in the model in a repeated time step, nominally representing a single working day:

1. Determine behaviours
2. Transmit norms

2.3.4 Design Concepts

Basic Principles

The model is designed to transparently reflect decision trees learned from questionnaire data, and hence the decision trees are hard-coded. It is intended to reflect the questionnaire as strictly as possible, and so only predicts the responses to the questions, not whether the corresponding pro-environmental behaviour is performed. It deviates from the questionnaire only in assigning a network structure to the norm interactions among agents, and interpreting normative influences on behaviour on the basis of model state rather than respondents' answers.

Emergence

What emerges from the model is the change in responses to behavioural questions associated with the dynamics imposed by the network structure and interpretation of norm influences.

Sensing

Agents sense the pro-environmental behaviours of their neighbours in the social network (descriptive norm).

Interaction

Agents may transmit and receive injunctive norms to/from each other.

Stochasticity

Used in building the social network during initialisation, and each time step in determining whether or not different kinds of norm transmission occur. Randomness is also used to determine the actual response from the discretised ranges at the leaf nodes (see Fig. 2), and in determining the order in which agents are activated each time step.

Observation

Data were collected on the time series of the distribution of predicted response for each behavioural variable, and the mean and variance of the difference between agents' predicted response at the beginning and end of the run.

2.3.5 Initialisation

The input file to the model is a CSV file with one row for each respondent to the questionnaire in the case study (in this case, an aggregation of data from three case studies), and one column for each question containing that respondent's answer or 'NA' if no answer was given. WERC-M Q uses this file (the location of which is specified using the questionnaire-data-file parameter) to initialise the agents' data attribute as a hash table of variable name to value.

The agents are then connected in a workplace social network implementing three relationship types: subordinate, co-worker and supervisor. Supervisor and subordinate relationships are implemented through the directed `manager` link network, in which A is a subordinate of B iff B is a supervisor of A. The workplace management hierarchy is determined by randomly selecting a single agent to be the chief executive of the artificial institution, assigning that agent a `level` of 1, setting a global variable `max-level` to 1, and then constructing the organogram as follows:

```
 1. While any agents have an unassigned level:
 2.   Let M = 0
 3.   For each agent A with level = max-level:
 4.     Let N = sample from a Poisson distribution with mean fan-out-mean
                                                          (a parameter)
 5.     If N > 0:
 6.       If the number of agents with unassigned level > N:
 7.         Let N = the number of agents with unassigned level
 8.       End If
 9.       For each of the N nearest agents B with unassigned level:
10.         Set level (of B) = max-level + 1
11.         Set M = M + 1
12.         Make a manager link from A to B
13.       End For
14.     End If
15.   End For
16.   If M > 0:
17.     Set max-level = max-level + 1
18.   End If
19. End While
```

Note that the code on lines 16–18 check that some agents have been assigned a `level` before increasing `max-level`. This effectively causes resampling of the Poisson distribution until agents have been assigned to the next level, and hence for low `fan-out-mean`, the distribution of subordinates of each supervisor may not quite be Poisson distributed.

The co-worker network is constructed using an adaptation of Hamill and Gilbert's [31] social circles model. The latter is argued by its authors to generate social networks that are more realistic than Watts and Strogatz's [32] small-world algorithm, or Barabási and Albert's [33] scale-free algorithm. Agents are randomly positioned in a 2D space, and then connected together if the distance between them is less than a parameter (`reach`). The adaptation of the algorithm used here imposes the further constraint on the prospective connection that the absolute difference in `level` between the pair of agents must be less than or equal to 1. The selection of the nearest agents in line 9 of the manager network construction algorithm is intended to ensure that this constraint during the construction of the co-worker network is affected as little as possible by the construction of the manager network.

2.3.6 Input Data

There are no time series input data for this model.

2.3.7 Submodels

Determine Behaviours

For each of the four behaviours (BW.6, BW.17, BW.19, BW.22), compute the result of the corresponding decision tree for each agent, with the following modifications:

1. Where the decision tree uses a descriptive norm in a branch conditional, use the mean of appropriately connected agents for that behaviour.
2. Where the decision tree uses an injunctive norm in a branch conditional, use the mean of the corresponding norm transmission decision for appropriately connected agents.
3. Where the decision tree uses the level in the organisation in a branch conditional, return 4 (operational) if `level` = `max-level`; 3 (supervisor) if `level` = `max-level`–1 and `max-level` > 3; 1 (top manager) if `level` = 1 or (`level` = 2 and `max-level` > 3); and 2 (manager) otherwise.
4. Where an agent has NA as the value of the variable in the branch conditional, use 0 (as was the case when the decision trees were constructed).
5. Where the decision tree used one of the hedonic, egoistic, altruistic or biospheric values questions in the branch conditional, use -10 as the value if the response was -1 (as was done when the decision trees were constructed).

Transmit Norms

These are assumed to occur less frequently than the everyday behaviours, each of which (driving efficiently when using a car on business or commuting, turning on heating or air conditioning, recycling plastic) could be thought of as occurring roughly once per day. Further, the frequency may depend on the relationship. The most frequent was assumed to be co-worker norm transmission, with probability 0.1 (corresponding roughly to once every two working weeks if the behaviours in

Table 1 Parameter settings varied in the exploration of model dynamics

Parameter	Values
`fan-out-mean`	1.5, 2, 5, 10, 20
`reach`	2, 4, 6, 8, 10

step one are seen as occurring daily), and the least frequent norm transmission to supervisors, with probability 0.05. Norm transmission to subordinates was given a probability of 0.075. Once a norm transmission had been determined to occur, the corresponding decision tree was used to determine the response, in exactly the same way as for the other behaviours in 'Determine behaviours' above.

2.4 Experiments with the Model

Experiments were conducted to investigate the effect of the network parameters `fan-out-mean` and `reach` on the predicted responses of the agents after 200 timesteps. The values for each are shown in Table 1, and certain combinations of them are visualised in Fig. 3. Each parameter setting was repeated 40 times. There were therefore 1000 runs of the model in total.

For each run, the model records in the last time step the mean and variance of the distribution of difference between each non-cloned agent's final and initial response to each behaviour. Specifically, for each behaviour, the NetLogo expressions for the means and variances are computed as shown in (1) and (2),

$$\texttt{mean}\ [\textit{behaviour} - \textit{initial-behaviour}]\ \texttt{of workers} \quad (1)$$

$$\texttt{variance}\ [\textit{behaviour} - \textit{initial-behaviour}]\ \texttt{of workers} \quad (2)$$

where *behaviour* and *initial-behaviour* are substituted for a lookup in the agent's `data` table for the corresponding behaviour variables at the end and beginning of the run respectively; and `workers` is the set of interacting agents.

In these experiments, we are primarily interested in knowing which of the variables in Table 1 had the greatest effect on the dynamics in the model. Our results are assessed using a Kruskal-Wallis test with the null hypothesis that there is no functional relationship between network parameters and the mean and variance of the difference between the initial and final predicted behaviour of each behaviour for each agent.

3 Results

The results are reported in Table 2 (mean difference in behaviour) and Table 3 (variance). For BW.6 (drive efficiently), which is effectively operating as a control,

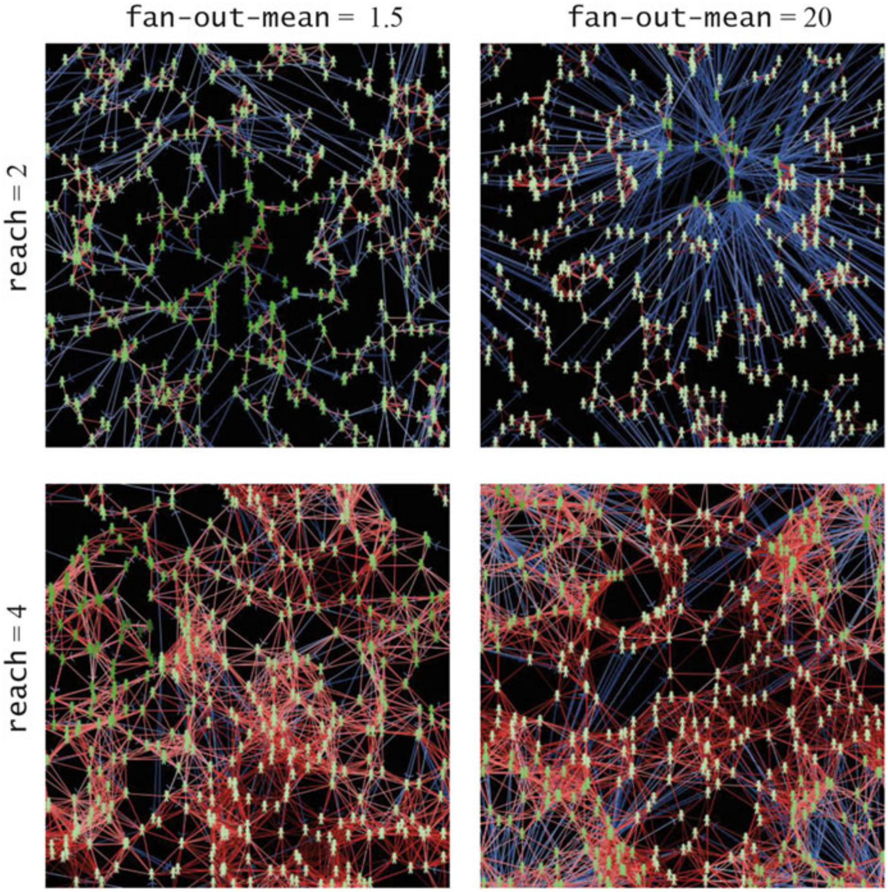

Fig. 3 Various visualisations of social networks derived from different parameters for the manager and co-worker networks. Agents are shown using *green 'person' icons*, with shade corresponding to the level in the organisation (darker is higher up, i.e. the agent's `level` attribute is closer to 1). *Blue links* show the manager network; *red links* show the co-worker network. Both are given a brighter shade of their respective colour if they have a higher mean norm transmission value along the link

it is apparent that neither network parameter has a significant effect on the difference between the initial and final predicted values from the BW.6 decision tree (Fig. 1). For behaviours BW.17 (turn on heating) and BW.22 (recycle plastic), which use the co-worker network, the `reach` parameter does have a significant effect on the mean difference, but not on the variance in the case of BW.22. As might be expected, where behaviours do not use co-worker norms, the `reach` parameter has no significant effect.

More interesting is the relationship between the use of the directed manager network in a behaviour, and the `fan-out-mean`. Norms from supervisors to

Table 2 Results for the Kruskal-Wallis tests of the effects of the network parameters `reach` and `fan-out-mean` on the mean difference between the initial and final predicted behaviour (rows) of each agent

Behaviour	Co-worker?	Manager?	`reach`	`fan-out-mean`
BW.6	–	–	–	–
BW.17	D	D±	***	–
BW.19	–	D−	–	*
BW.22	I	D+	**	**
NT.1	–	D+	–	***
NT.2	–	I+	–	***
NT.3	–	D − I−	–	***

The Co-worker? and Manager? columns show whether any of the explanatory variables in each behaviour's decision tree use descriptive (D) or injunctive (I) norms. In the directed Manager network, a + means norms from subordinates, and – (after D or I) norms from supervisors. BW.6 is driving efficiently, BW.17 turning on the heating, BW.19 turning on the air conditioning, and BW.22 recycling plastic. NT.1 is norm transmission to subordinates, NT.2 to co-workers, and NT.3 to supervisors
*$P<0.05$; **$P<0.01$; ***$P<0.001$

Table 3 As per Table 2, but for the variance of the distribution of differences of the initial and final predicted behaviours of each agent

Behaviour	Co-worker?	Manager?	reach	fan-out-mean
BW.6	–	–	–	–
BW.17	D	D±	***	**
BW.19	–	D−	–	*
BW.22	I	D+	–	***
NT.1	–	D+	–	***
NT.2	–	I+	–	***
NT.3	–	D − I−	–	***

subordinates (indicated by a D– or I– in the Manager? column of Tables 2 and 3) affect larger numbers of individuals than vice versa (D+ or I+), as in the model, individuals only ever have one supervisor. A larger `fan-out-mean` will increase the effect a single supervisor can have, whilst a smaller `fan-out-mean` will increase the effect a single subordinate can have.

In the case of BW.19 (turn on air conditioning), which only uses descriptive norms from supervisors to subordinates, the effect of `fan-out-mean` is weakly significant on both mean and variance (and indeed, given the number of significance tests done, a possible type I error). By contrast, NT.3 (norm transmission to supervisors), which uses descriptive and injunctive norms from supervisors to subordinates, has a strongly significant effect of `fan-out-mean`. BW.22, NT.1 (norm transmission to subordinates) and NT.2 (norm transmission to co-workers) all use only norms (descriptive in the cases of BW.22 and NT.1, and injunctive in the case of NT.2) from subordinates to supervisors, and yet still feature significant effects of `fan-out-mean` on both mean and variance. BW.17 is interesting in that

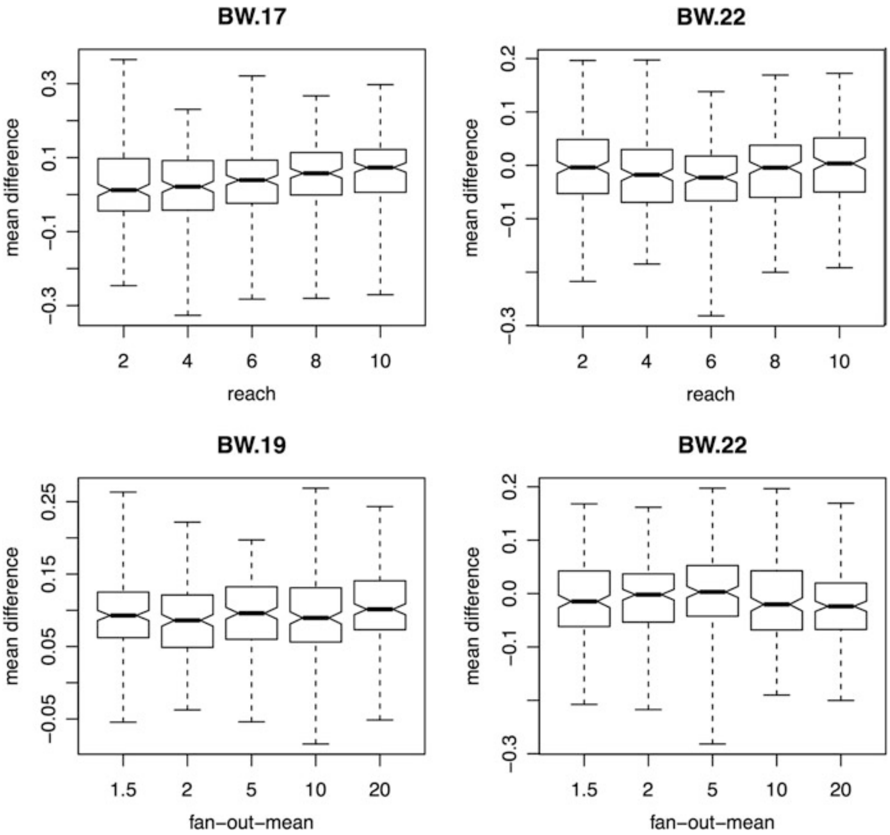

Fig. 4 Boxplots of the distributions of mean difference between initial and final predicted behaviour for those parameter and behaviour combinations for which a significant effect is shown in Table 2. The *thick lines* show the medians, whilst the *bottom* and *top of the boxes* are drawn at the first and third quartiles. The whiskers (*dashed lines*) extend to the minimum and maximum. The notches in the size of the box extend to ±1.58 times the interquartile range divided by the square root of the sample size, as described in the help file for `boxplot.stats` in R, the statistical software used to draw the boxplots. As this text asserts, these notches show approximately a 95 % confidence interval for the purposes of comparing pairs of medians—if notches do not overlap, this is potential evidence of a significant difference in median

it features descriptive norms in both directions of the manager network, but no effect of `fan-out-mean` on the mean difference in predicted behaviour at the start and end of the run, though there is a significant difference in the variance.

There is therefore no clear pattern in whether norms from subordinates or supervisors are more or less effective in changing behaviour (for better or for worse) as the corporate hierarchy is adjusted. Neither is there any discernible pattern in whether injunctive or descriptive norms have a stronger effect, which is interesting since injunctive norms require norm transmission. Though this may be in part due to insufficient behaviours being studied to enable any such patterns to be observed, there are also questions of how norms are used by the decision trees themselves, and how sensitive they are to the attributes of agents being put in particular positions in the network. However, it should be no surprise that different behaviours will be sensitive in different ways to the topologies of norm interaction.

The Kruskal-Wallis test merely shows there is a functional relationship, but says nothing about the magnitude or direction of the effect. In Fig. 4, boxplots are used to show the distribution of the mean difference in behaviour for BW.17 and BW.22 in the case of `reach`, and for BW.19 and BW.22 in the case of `fan-out-mean` (these being the significant results in the first four rows of Table 2). Bearing in mind that responses vary from 1 to 7, the scaling on the y-axes of these graphs show that the magnitude of effect is small. Further, there is considerable overlap, especially when the extremes (whiskers) are included. However, Kaiser [34] proposes a nonlinear (logistic) formalisation of Campbell's [35] paradigm for assessing the attitude-behaviour gap. If this can be used to determine the probability of performing a behaviour from its reported frequency on a Likert scale, then, depending on the mean response level, small differences such as those reported here could have a larger effect on the performance of the actual behaviour.

BW.17 shows an increasing trend with respect to `reach`, as does BW.19 (though less clearly, which may explain the weak significance of this result) with respect to `fan-out-mean`. The wording of both these behaviours is such that an increase in response means less pro-environmental behaviour, since, respectively, they refer to turning the heating and air-conditioning on. The trends in the case of BW.22 (in which a positive difference does mean more pro-environmental behaviour—recycling plastic) are for a U-shaped curve in the case of the `reach` parameter, and an inverted-U for `fan-out-mean`. These shapes are also seen in the distributions of `fan-out-mean` against mean difference for each of the norm transmission behaviours (Fig. 5). Since BW.22 uses injunctive norms in the co-worker network, this may explain the U-shaped relationship between `reach` and mean difference observed in the top right boxplot in Fig. 4. The presence of U and inverted-U curves in the relationship between `fan-out-mean` and mean difference may reflect the observations above about the balance between `fan-out-mean` and the relative effectiveness of norms from subordinates and supervisors.

In general, the observations in Figs. 4 and 5 lend weight to the conclusions from the study of the results of the significance tests: the topologies of norm interactions affect different behaviours in different ways.

4 Discussion

Our hypothesis has been that, where behaviours are affected by various workplace norms, the topology of social interactions is influential. The results have indeed shown that (with the exception of BW.6 (drive efficiently), which was not found to be affected by norms using CFS-MDL-DT) the co-worker and manager network topology both have a small but significant effect on the dynamics implied by norm transmission and injunctive and descriptive norms in a static questionnaire pertaining to everyday pro-environmental behaviours in the workplace. The effect is context-sensitive: it changes according to the behaviour in question. Nevertheless, the implication for social and environmental psychology is that empirical findings should include a discussion of the structure of the social network, and for empirical agent-based modelling, that data are needed on the topology of social interactions as well as on the behaviours themselves.

Choi et al.'s [36] exploration of innovation diffusion (which is similar to norm diffusion insofar as it is imitative) found that random networks are a more difficult medium in which to transmit information from a low level of initial adoption, because the lack of cliques means there is not enough accumulation of adopters among the connections of later adopters for them to adopt. However, once the number of initial adopters is high enough, random networks diffuse much more rapidly than cliquey ones (ibid.). We have not studied the effect of changing the initial response—this could be done in future work—however, we did measure the global clustering co-efficient from the model (the proportion of triplets that are closed). This isn't quite the same as cliques (which are subgraphs with fully connected nodes), but will be related to it as more and larger cliques will mean more closed triplets. As Fig. 6 shows, there is no clear trend in the relationship between clustering coefficient and mean difference for BW.22 (one of the two behaviours for which `reach` had a significant effect), though the range of coefficients resulting from the parameters used in this study does not cover the full span of values from [0, 1].

Empirical findings [37] suggest that descriptive norms may be affected by relationship type. Specifically, co-workers performing pro-environmental behaviours have been found to make it more likely that individuals will also do so, whilst managers not performing pro-environmental behaviours have been found to make it more likely that individuals will also not do so. The data reported from our model

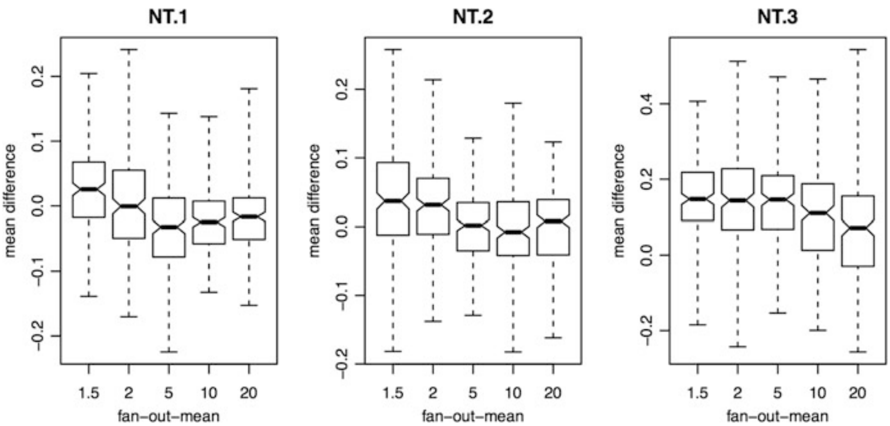

Fig. 5 As per Fig. 4, but for the bottom three rows of Table 2

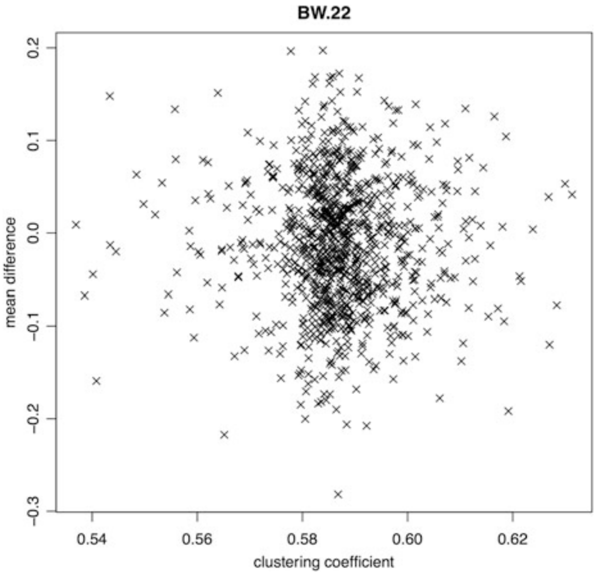

Fig. 6 Scatter plot of clustering coefficient against mean difference for BW.22 (recycling plastic)

do not allow us to determine whether this finding is upheld, but we do see in our results different dynamics in the effect of the `fan-out-mean` parameter of the mean difference and that of the `reach` parameter (where it uses only descriptive norms), the former having a monotonic effect on the mean difference, the latter a U or inverted-U shape to the relationship. The effects observed by Keiser et al. [37] should emerge from the model, rather than being imposed. Confirming this, and the differing dynamics in the hierarchical and co-worker networks, would be the possible subjects of future work.

As stated above, it would be better in empirical modelling work to gather data on the actual topology of interactions rather than generating the networks artificially. Though established methods, such as social network analysis [38] and theory, such as actor network theory [39], are available to explore interactions and networks in the social sciences, these tend to be applied by rather specialised communities. A search in the Thomson Reuters database of manuscripts published in 2012 returned less than 250 results for "snowballing" (a method used in the social network community), but over 130,000 results for the more standard tools of the social sciences: interviews and questionnaire surveys. Ours is far from being the first article in the modelling community to highlight the significance of interactions in a set of results. With a greater interest in empirical agent-based modelling [16], developing cost-effective approaches to gathering evidence to support modelling of interactions is a priority. We anticipate that such approaches, if widely used, would provide an interesting context in which to evaluate findings from studies in the social sciences, even when not involving modellers.

Gilbert [40] is critical of the use of survey data in agent-based models, pointing out that they fail to adequately address interactions with others and are a sample from a snapshot in time. Outright rejection of sampling approaches constrains the scope for collaborations needed to build empirical agent-based models, as individual researchers have their preferred tools. We have shown here that, with a few extra questions on norm transmission, it was possible to create an empirical agent-based model with dynamic behaviour that is based on questionnaire data. Although the results suggest that further data are needed on social network structure, in general we may reasonably expect some adaptation of traditional social science tools to be needed when they are to be applied (at least in part) to the development of agent-based models.

The model has used decision trees learned from questionnaire data as a means for representing agents' decisions. Although the structure of these trees is fixed, some dynamism in individual decision-making processes is enabled through the modification of explanatory variables. Here, these were purely those pertaining to descriptive and injunctive norms, but demographic characteristics (e.g. age), training, career progression and workplace re-organisation could all affect the route taken by an individual agent through the decision tree. There is no theoretical reason why decision trees could not have nodes depending on memory, which would provide a basis for implementing learning. However, gathering enough empirical data to build such a tree could prove challenging. The main advantage of decision trees in terms of their relationship with the empirical data is their transparency, and it is unsurprising that they have been used in other ABM work, empirical and otherwise (e.g. [41, 42]), with Verhagen [43] applying them to the learning of norms. An important issue with decision trees, where derived automatically from empirical data, is that their structure can be sensitive to the algorithm used to build it. Here, we have used an approach to decision tree construction found by Sánchez-Maroño et al. [25] mostly to minimise classification or validation error, though since we are primarily interested in demonstrating the principle of using decision trees to study norms in agent-based models, such errors are of less concern. Other researchers have found it is sometimes appropriate to refine the model qualitatively (e.g. [44, 45]), and this would be appropriate here, though if modelling all the behaviours in the questionnaire, modifying all the trees in this way would place a considerable burden on the research team. Again, our primary concern with demonstrating the principle has meant this step was not undertaken.

5 Conclusion

Agent-based modelling is predicated on the importance of individual heterogeneity and interactions in determining society-level outcomes. This work has shown that adding the norm dynamics implied in static questionnaire data affects the results thereof in ways that are sensitive to network topology parameters for both hierarchical and co-worker networks. Although this knowledge could be used to calibrate network construction parameters (particularly when combined with two-shot questionnaires), gathering data on networks and relationships is clearly an important part of an empirical agent-based modelling project. Indeed, the influence network properties have on the dynamics suggests that social network information should be relevant to all empirical work in the social sciences.

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A.1 Appendix: Netlogo Code

The `get-value-of` procedure, called from the code shown in Fig. 2, implements the rules described in the submodels in the ODD in Sect. 2.3 as shown below. References to injunctive and descriptive norms are highlighted in `inverse video`. One detail not discussed in the text is the possibility that there are no co-workers, supervisors (for the top manager) or subordinates (for those at the bottom of the hierarchy). In this case, the treatment is the same as for ‘NA’: 0 is returned as the value of the variable. Another is that when assessing the descriptive norm, two of the behaviours (turning on the heating (BW.17) and turning on the air conditioning (BW.19)) are worded such that higher responses mean less pro-environmental behaviour. When reporting a descriptive norm (most of my colleagues behave pro-environmentally at work), the responses of colleagues for these behaviours need to be inverted so that they correspond to the sense used in the descriptive norm question.

```
to-report get-value-of [ var behav ]
 if (var = "Q4") [
   ; Use level in virtual organisation
   report ifelse-value (level = max-level) [4] [
     ifelse-value (level = max-level - 1 and max-level > 3) [3] [
       ifelse-value (level = 1
                     or (level = 2 and max-level > 3)) [1] [2]
     ]
   ]
 ]
 if (length var > 4 and substring var 0 4 = "NIL.") [
   ; Handle injunctive norms
   if var = "NIL.1" [
     if not any? out-manager-neighbors
       with [is-number? table:get data "NT.3"] [
       report 0
     ]
     ; Most of my subordinates think I should behave
     ; pro-environmentally...
     report mean [table:get data "NT.3"] of out-manager-neighbors
       with [is-number? table:get data "NT.3"]
     ; ... so use norm transmission to supervisors of those I
     ; manage
   ]
```

```
    if var="NIL.2" [
      if not any? co-worker-neighbors
        with [is-number? table:get data "NT.2"] [
        report 0
      ]
      ; Return transmission from co-workers
      report mean [table:get data "NT.2"] of co-worker-neighbors
        with [is-number? table:get data "NT.2"]
    ]
    if var="NIL.3" or var="NIL.4" [
      if not any? in-manager-neighbors
        with [is-number? table:get data "NT.1"] [
        report 0
      ]
      ; Return transmission from supervisors
      report mean [table:get data "NT.1"] of in-manager-neighbors
        with [is-number? table:get data "NT.1"]
    ]
  ]
  if (length var>4 and substring var 0 4="NDL.") [
    ; Handle descriptive norms
    let desc-norm 0
    if var="NDL.1" [
      ; Return typical behaviour of subordinates (use behav)
      if not any? out-manager-neighbors
        with [is-number? table:get data behav] [
        report 0
      ]
      set desc-norm mean [table:get data behav] of
        out-manager-neighbors with [is-number? table:get data behav]
    ]
    if var="NDL.2" [
      if not any? co-worker-neighbors
        with [is-number? table:get data behav] [
        report 0
      ]
      ; Return typical behaviour of co-workers (use behav)
      set desc-norm mean [table:get data behav] of
        co-worker-neighbors with [is-number? table:get data behav]
    ]
    if var="NDL.3" or var="NDL.4" [
      if not any? in-manager-neighbors
        with [is-number? table:get data behav] [
        report 0
      ]
      ; Return typical behaviour of supervisors (use behav)
      set desc-norm mean [table:get data behav]
        of in-manager-neighbors
        with [is-number? table:get data behav]
    ]
    ifelse (behav="BW.17" or behav="BW.19") [
      ; Here 'behaving pro-environmentally' is behav=1
      report 8 - desc-norm
    ]
```

```
    [
      ; Here 'behaving pro-environmentally' is behav=7
      report desc-norm
    ]
  ]
  if table:get data var="NA" [
    report 0
  ]
  if substring var 0 1="V" and table:get data var=-1 [
    report -10
  ]
  report table:get data var
end
```

The code in Fig. 2 implements a behaviour (BW.6—drive efficiently) that does not use injunctive or descriptive norms. The procedure below implements the behaviour for recycling plastic (BW.22), which uses both injunctive and descriptive norms (highlighted in `inverse video`) in various branches:

```
to-report dt-recycle-plastic
report ifelse-value (get-value-of "Country" "BW.22"<= 2) [
  ifelse-value (get-value-of "IES.2" "BW.22"<= 3) [
    0.7+random-float 0.7
  ] [
    ifelse-value (get-value-of "WV.5" "BW.22"<= 4) [
      ifelse-value (get-value-of "IES.3" "BW.22"<= 6) [
        ifelse-value (get-value-of "IES.2" "BW.22"<= 5) [
          ifelse-value (get-value-of "IES.2" "BW.22"<= 4) [
            ifelse-value (get-value-of "VE.1" "BW.22"<= 0) [
              0.7+random-float 0.7
            ] [3.5+random-float 3.5]
          ]
          [2.8+random-float 0.7]
        ]
        [0.7+random-float 0.7]
      ]
      [3.5+random-float 3.5]
    ]
    [
      ifelse-value (get-value-of "VE.1" "BW.22"<= 2) [
        ifelse-value (get-value-of "IES.3" "BW.22"<= 5) [
          ifelse-value (get-value-of "IES.2" "BW.22"<= 6) [
            ifelse-value (get-value-of "WV.5" "BW.22"<= 6) [
              ifelse-value (get-value-of "NDL.1" "BW.22"<= 1) [
                ifelse-value (get-value-of "IES.2" "BW.22"<= 5) [
                  ifelse-value (get-value-of "VE.1" "BW.22"<= 1) [
                    ifelse-value (
                      get-value-of "IES.3" "BW.22"<= 4) [
                      ifelse-value (
                        get-value-of "NIL.2" "BW.22"<= 1) [
                        0.7+random-float 0.7
                      ] [1.4+random-float 0.7]
                    ]
                    [
```

```
              ifelse-value (
                get-value-of "Q5" "BW.22" <= 1) [
                1.4 + random-float 0.7
              ] [0.7 + random-float 0.7]
            ]
          ]
          [
            ifelse-value (
              get-value-of "IES.2" "BW.22" <= 4) [
              3.5 + random-float 3.5
            ] [0.7 + random-float 0.7]
          ]
        ]
        [0.7 + random-float 0.7]
      ]
      [3.5 + random-float 3.5]
    ]
    [
      ifelse-value (get-value-of "NDL.1" "BW.22" <= 1) [
        ifelse-value (get-value-of "SE.2" "BW.22" <= 3) [
          ifelse-value (get-value-of "VE.1" "BW.22" <= 0) [
            1.4 + random-float 0.7
          ] [0.7 + random-float 0.7]
        ]
        [3.5 + random-float 3.5]
      ]
      [0.7 + random-float 0.7]
    ]
  ]
  [0.7 + random-float 0.7]
]
[
  ifelse-value (get-value-of "SE.2" "BW.22" <= 6) [
    ifelse-value (get-value-of "IES.3" "BW.22" <= 6) [
      ifelse-value (get-value-of "Q3" "BW.22" <= 4) [
        ifelse-value (get-value-of "VE.1" "BW.22" <= -10) [
          ifelse-value (get-value-of "NIL.2" "BW.22" <= 4) [
            ifelse-value (
              get-value-of "WV.5" "BW.22" <= 6) [
              3.5 + random-float 3.5
            ] [0.7 + random-float 0.7]
          ]
          [0.7 + random-float 0.7]
        ]
        [
          ifelse-value (get-value-of "VE.1" "BW.22" <= 1) [
            3.5 + random-float 3.5
          ] [2.8 + random-float 0.7]
        ]
      ]
      [
        ifelse-value (get-value-of "SE.2" "BW.22" <= 3) [
          0.7 + random-float 0.7
        ] [3.5 + random-float 3.5]
```

```
             ]
           ]
           [
             ifelse-value (get-value-of "NIL.2" "BW.22"<= 5) [
               ifelse-value (get-value-of "NIL.2" "BW.22" < = 3) [
                 0.7 + random-float 0.7
               ] [3.5 + random-float 3.5]
             ]
             [0.7 + random-float 0.7]
           ]
         ]
         [3.5 + random-float 3.5]
       ]
     ]
     [3.5 + random-float 3.5]
   ]
 ]
]
[3.5 + random-float 3.5]
end
```

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