An agent-based model of cultural change for a low-carbon transition

Keywords: cultural evolution, opinion dynamics, environmental identity, behavioural diffusion, green influencers

Extended Abstract

Meeting climate goals requires radical changes in the consumption behaviours of individuals. Theoretical models of behavioural change can provide insight into what barriers and drivers exist to the adoption of low-carbon lifestyles. A crucial element in the study of a transition towards low-carbon lifestyles is how quickly behaviours in a population, and even culture itself, will change. A good understanding of the relation between culture and behaviours can help to avoid potential lock-in toward brown alternatives.

The application of cultural evolution to the issue of transition studies is a nascent area of research (Davis et al. 2018; Kaaronen and Strelkovskii 2020). It lacks detail on the spread of multiple traits simultaneously over the same population. A multi-dimensional perspective, such as the cultural chromosome proposed by Epstein and Axtell (1996), is key given the breadth of lifestyle changes required for deep decarbonisation. This approach centres on the role of inter-behaviour spill-overs in adoption dynamics, where the uptake of one green behaviour may lead to a self-perception of a greater green identity, with a stronger environmental identity making pro-environmental behaviour more probable (Van der Werff et al. 2014).

We develop an agent-based model to study how the diffusion of pro-environmental behaviours interacts with longer-term cultural evolution. The model structure is shown in Figure 1. Individuals $n = 1, ..., N$, each have multiple continuous environmentally related behaviours $m = 1, ..., M$ that evolve over discrete time t = $0, ..., \tau$. Taking inspiration from the Theory of Planned behaviour (Ajzen 1991), we model the extent to, or frequency with which, a behaviour is performed as a balance between a socially influenced behavioural attitude $A_{t,n,m}$, against a static threshold. Each behaviour is represented as a one-dimensional continuous parameter between extremes of a zero-emissions green choice and maximally emissive brown reference. The behavioural attitudes spread through a fixed Watts–Strogatz graph via social interactions with their K_n neighbours. Using the definition of culture as socially transmitted information, we represent individuals' environmental identity $I_{t,n}$, as an aggregation of attitudes over a total of M environmentally relevant behaviours. The strength of interaction between individuals is determined by the similarity in their environmental identity. Thus the presence of culture, in the form of an environmental identity, leads to inter-behavioural dependency and spillovers in green attitudes. We represent from whom an individual learns and how much attention is paid with the social network weighting matrix $\alpha_{t,n,k}$ given by the softmax function

$$\alpha_{t,n,k} = \frac{e^{-\theta|I_{t,n}-I_{t,k}|}}{\sum_{j\neq n}^{K_n} e^{-\theta|I_{t,n}-I_{t,j}|}}, \tag{1}$$

where θ is parameter measuring confirmation bias, j is a dummy variable, and the weight is inversely related to the identity distance between individuals and their K_n neighbours in the social network.

Our sensitivity analysis results show that the initial distribution of agent attitudes towards behaviours and asymmetries in social learning caused by confirmation bias are the main drivers of model dynamics. To further explore the effect of confirmation bias on identity dynamics we look at the bifurcation process of clusters of behavioural attitudes at the end of experiments, shown in the left panel of Figure 2. For increasing confirmation bias, we use a Gaussian kernel density estimator to group individuals based on the final attitude towards their first $m = 1$ of three $M = 3$ environmentally related behaviours. Larger values of confirmation bias produce greater fragmentation in attitudes.

A cornerstone of the model is the role of culture, approximated as environmental identity, in the diffusion of pro-environmental behaviours. To investigate this effect we perform the same bifurcation analysis but now for the case of behavioural independence, see the right panel of Figure 2. For these bifurcation experiments, the social network weighting in Equation 1 is now determined by the behavioural attitude distance, $|A_{t,n,m} - A_{t,k,m}|$, not the identity distance. This results in one weighting matrix for each m behaviours, $\alpha_{t,n,k,m}$ and the diffusion of attitudes occurring independently for each behaviour. Relative to the behavioural independence case, environmental identity stimulates the convergence of opinions by allowing individuals of more diverse behavioural backgrounds to relate themselves better to their peers and imitate their behaviour.

To assess the impact of culture beyond a purely diffusive regime, we introduce green influencers as a minority of individuals who broadcast a green attitude. Figure 3 shows that the decarbonisation impact of the green influencer is greatest when the initial attitude distance between non-influencers and green influencers is small enough to allow them to remain relevant in social interactions but great enough for there to still be large behavioural decarbonisation potential through solely attitude change. With the inclusion of culture, green influencers overcome larger distances in attitude between them and non-influencers, by leveraging similarities with their environmental identity to spread their message to a wider audience. This indicates the need for individual-specific information provision policies to avoid alienating those who might be inert to pro-environmental information if it is too green. However this green influencer minority fails in achieving deep decarbonisation through solely voluntary action, with a maximum emissions reduction of 12%. The combination of cultural change and policy instruments like carbon pricing is able to achieve higher levels of emissions reduction. We will study this in subsequent research.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2):179–211.

Davis, T., Hennes, E. P., and Raymond, L. (2018). Cultural evolution of normative motivations for sustainable behaviour. *Nature Sustainability*, 1(5):218–224.

Epstein, J. M. and Axtell, R. (1996). *Growing artificial societies: social science from the bottom up*. Brookings Institution Press.

Kaaronen, R. O. and Strelkovskii, N. (2020). Cultural evolution of sustainable behaviors: Pro-environmental tipping points in an agent-based model. *One Earth*, 2(1):85–97.

Van der Werff, E., Steg, L., and Keizer, K. (2014). I am what i am, by looking past the present: the influence of biospheric values and past behavior on environmental self-identity. *Environment and behavior*, 46(5):626–657.

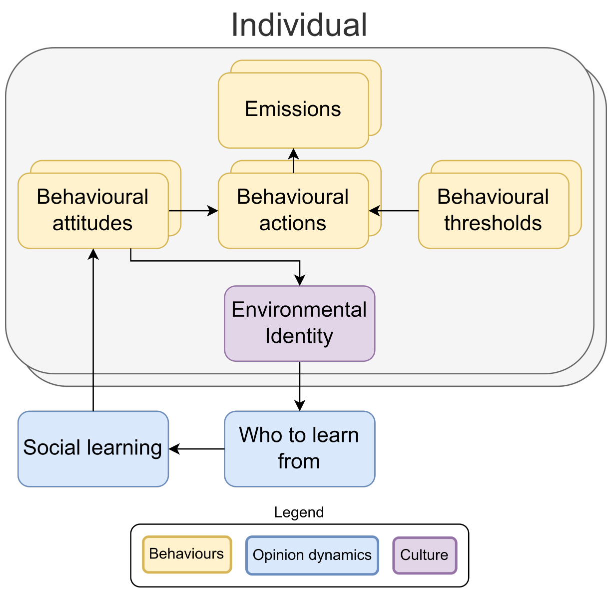

Figure 1: Model structure. Arrows indicate the direction of influence between components and stacked boxes represent a behavioural vector. Individuals $n = 1, \ldots, N$, each have multiple continuous environmentally related behaviours $m = 1, \ldots, M$ that evolve over discrete time t = $0, \ldots, \tau$. The past attitude $A_{t,n,m}$, of an individual towards multiple behaviours, determines a single environmental identity $I_{t,n}$. This in turn influences the transmission bias present, i.e. who an individual pays attention to when learning socially. Individuals have heterogeneous initial attitudes and thresholds towards multiple behaviours.

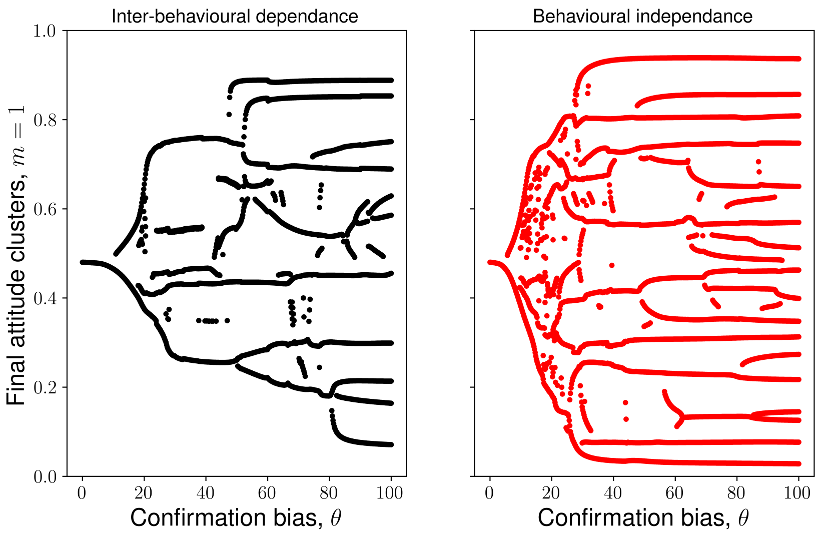

Figure 2: Bifurcation diagram showing the effect of increasing confirmation bias on the location of final attitude clusters of the first, of a total of three behaviours, with (black, inclusion of culture) and without (red) inter-behavioural dependency. For the latter, fragmentation in attitudes occurs at much lower values of confirmation bias, relative to the former. The location of these attitude clusters is determined using a Gaussian kernel density estimator with a bandwidth of 0.01. All experiments use the same initial seed to account for stochastic effects and the same degree of polarisation in initial attitudes.

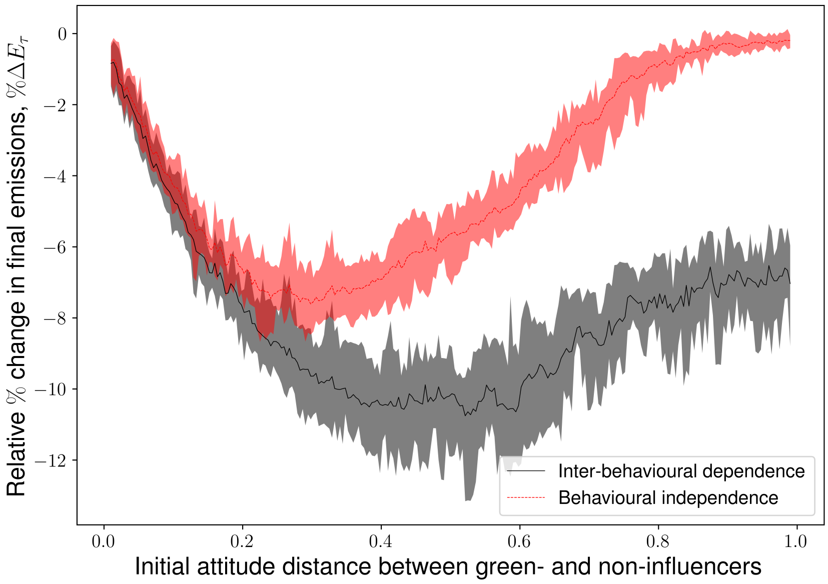

Figure 3: The relative percentage change in emissions between scenarios with and without green influencers, for cases with (black, inclusion of culture) and without (red) inter-behavioural dependency. This is measured for 256 mean initial attitude distances between non-influencers individuals and green influencers. The shaded region is the maximum and minimum values for the emissions' change over 10 experiments with different initial stochastic seeds. The experiments are run for 200 individuals, with an additional 20 green influencers, adjusting the mean number of agent neighbours K to 22 from 20 for constant network density.