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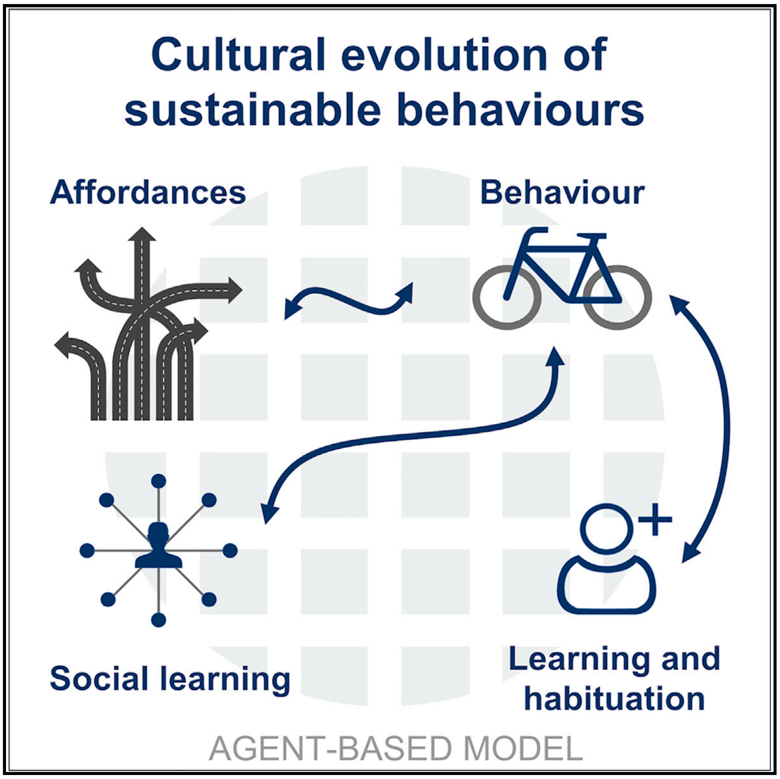
Cultural Evolution of Sustainable Behaviors: Pro-environmental Tipping Points in an Agent-Based Model

Graphical Abstract



Highlights

- An ABM is used to study the cultural evolution of sustainable behaviors
- Behaviors emerge as a function of affordances, social learning, and habits
- The affordances in an environment have a major effect on behavior adoption
- The ABM is validated against cycling behaviors in Copenhagen

Authors

Roope Oskari Kaaronen,
Nikita Strelkovskii

Correspondence

roope.kaaronen@helsinki.fi

In Brief

Kaaronen and Strelkovskii have designed an agent-based model to study the cultural evolution of sustainable behaviors. Behaviors emerge as a product of personal, environmental, and social factors. Particularly the structure of the environment has an effect on the adoption of pro-environmental behaviors. Even linear changes in pro-environmental affordances (action opportunities) can trigger non-linear collective behavior change. The model is validated against cycling behaviors in Copenhagen. This model gives further justification for policies and urban design that make pro-environmental behavior psychologically salient, accessible, and easy.

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Cultural Evolution of Sustainable Behaviors: Pro-environmental Tipping Points in an Agent-Based Model

Roope Oskari Kaaronen[1,2,3,*] and Nikita Strelkovskii[2]
[1]University of Helsinki, Faculty of Social Sciences, Helsinki Institute of Sustainability Science, University of Helsinki, Unioninkatu 37, PO Box 54, 00014 Helsinki, Finland
[2]International Institute for Applied Systems Analysis, Advanced Systems Analysis, Schlossplatz 1, 2361 Laxenburg, Austria
[3]Lead Contact
*Correspondence: roope.kaaronen@helsinki.fi
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SCIENCE FOR SOCIETY To mitigate climate change and safeguard ecosystems, we now more than ever require drastic change in behavior patterns. An urgent challenge is for humans to collectively adopt pro-environmental habits, including sustainable consumption and transport behaviors. However, there is only so much that individuals can do if sufficient opportunities for behaving sustainably do not exist. Therefore, we must understand how pro-environmental behaviors emerge systemically as a product of infrastructural, social, and individual factors. Using an agent-based model—a computational method for simulating interactions between individuals and environments—we illustrate how providing opportunities for pro-environmental behaviors (such as cycling infrastructure) can lead to the rapid adoption of sustainable habits (e.g., cycling). Our results are relevant for urban designers and policy makers given that we illustrate how even minor changes in everyday environments can trigger longstanding behavioral change.

SUMMARY

To reach sustainability transitions, we must learn to leverage social systems into tipping points, where societies exhibit positive-feedback loops in the adoption of sustainable behavioral and cultural traits. However, much less is known about the most efficient ways to reach such transitions or how self-reinforcing systemic transformations might be instigated through policy. We employ an agent-based model to study the emergence of social tipping points through various feedback loops that have been previously identified to constitute an ecological approach to human behavior. Our model suggests that even a linear introduction of pro-environmental affordances (action opportunities) to a social system can have non-linear positive effects on the emergence of collective pro-environmental behavior patterns. We validate the model against data on the evolution of cycling and driving behaviors in Copenhagen. Our model gives further evidence and justification for policies that make pro-environmental behavior psychologically salient, easy, and the path of least resistance.

INTRODUCTION

From decades of research in social and ecological psychology, cognitive science, ecology, and cultural evolution, we know this much about human behavior: our niche affords varieties of behaviors;[1–4] behaviors modulate personal states, such as habits, skills, or attitudes;[3,5,6] personal states influence behaviors;[6,7] behaviors alter environments;[3,8,9] and behaviors are socially learned and transmitted.[10,11]

However, what seems much less understood is how all these processes work in tandem to shape the evolution of socio-cultural and socio-ecological systems. Understanding this is important given that we require systemic change in human behaviors, cultures, and habits to reach the Sustainable Development Goals, to mitigate climate change, and to guard biodiversity and the ecosystems we inhabit.[2,12] Given the widespread demand for sustainable systemic change, particularly in the social and political sciences, it is curious how little is understood about how to instigate non-linear systemic change by means of environmental or urban policy and design. If we wish to reach social tipping points in the adoption of sustainable behaviors, we arguably need to better understand the mechanisms of their emergence. Formal models can be useful in exploring these mechanisms.[12]

Reaching social tipping points is an elusive yet imperative target. Often the assumption appears to be that whatever instigates this transition should roughly follow an S-shaped curve:[13] we should reach peak emissions as soon as possible, follow this with an increasingly fast decarbonization or phase-out, and then arrive at a new phase state by mid- to late 21st century. Or alternatively, we should adopt new sustainable habits or technologies at an accelerating rate until we reach a sustainable state of behavior.

Recently, it has been proposed that the design of pro-environmental affordances (action opportunities) could present us with an efficient leverage point to reaching tipping points in social systems and that affordances can induce positive-feedback loops in the collective adoption of behaviors.[2,14] We define affordances here as the behavioral opportunities afforded by the environment to an organism (e.g., bicycles and bicycle lanes afford cycling; see Model Assumptions). Therefore, our motivation is to study how the introduction of pro-environmental affordances to a social system can have non-linear effects on the collective adoption of sustainable behavioral patterns. This is a politically important objective because illustrating how the introduction of environmentally friendly infrastructures can trigger social tipping points gives further justification for investing into the design of urban and everyday environments that make pro-environmental behavior psychologically salient, easy, and the "the path of least resistance and the default form of life."[2] Although predicting where or when pro-environmental tipping points emerge remains a difficult, if not impossible,[15] task, if we ever wish to reach them, it is important to understand the mechanisms underlying their emergence.

The research questions of this article are, where do the (politically feasible) leverage points lie in tipping collective behavioral patterns of a social system from one state to another, and more specifically, how can the composition of the "landscape of affordances"[4] of a socio-ecological niche affect the evolution and emergence of collective behavioral patterns? The landscape of affordances simply means the set of affordances available in an ecological niche[4] (see Environment Affords Behavior).

Our methodological approach is agent-based modeling. We argue that agent-based modeling is particularly suitable for dealing with our research questions given that agent-based models (ABMs) by definition are used to model agent-agent and agent-environment interactions and their evolution over time.[16] Our conceptual model also includes other characteristics particularly suitable for ABMs, such as heterogeneous populations and emergent collective behaviors arising from simple interactions.[16,17] Agent-based modeling has become a standard method for studying complex, dynamical, and adaptive systems,[16,17] presenting social and behavioral scientists with new avenues for studying human and social behavior from systems perspectives. We use NetLogo, a "low-threshold and no-ceiling" modeling software,[18] for modeling.

ABMs have previously been employed in studying the adoption of various sustainable behaviors and attitudes,[19] including models of norm transmission and evolution,[20,21] recycling,[22] traffic and transport,[23–25] farming,[26] energy and risk management,[27,28] and psychology.[29,30] Our contribution to this rapidly developing field is in developing a holistic systemic approach to the emergence of behavior as a subtle function of social, individual, and environmental factors by focusing explicitly on the emergent leverage points and tipping points. Our model illustrates both how system-level emergent phenomena constrain and enable individual and group behaviors and how individual and group behaviors can shape these constraints and affordances. Our results are relevant for urban designers and other policy makers interested in instigating collective pro-environmental patterns of behavioral change.

Here, we propose a dynamical and complex systems approach to the study of the cultural evolution of human behaviors. We develop an ABM to illustrate how self-reinforcing cultures of behavior can emerge from five interconnected processes, which together form an "ecology of human behavior," as hypothesized by Kaaronen.[2] First, ecological information in a physical and socio-cultural environment specifies affordances or psychologically salient opportunities for behavior. Second, behavior modulates the personal states of humans through processes of individual learning and habituation. Third, personal states—such as habits, intentions, and attitudes—shape behavior. Fourth, behavior alters the environment in non-random ways through processes of cultural niche construction. Fifth and finally, all behaviors occur in a social network and result in social learning and transmission (through, e.g., teaching or copying). Together, these five processes form a dynamical system, or "a system whose behavior evolves or changes over time."[31] We expand Kurt Lewin's equation (Equation 1),[32] a classic heuristic formula in social psychology where behavior (B) is a function (f) of the person (P) and their environment (E), to include the aforementioned five feedback loops. See Figure 1 and Table 1 for our conceptual model. Our approach allows us to study a social system's various leverage points, or "places in the system where a small change could lead to large shift" in the system's behavior.[33]

$$\text{Lewin's equation}: \; B = f(P, E) \qquad \text{(Equation 1)}$$

RESULTS

Overview

In this section, we present the results of our agent-based simulations, where behavior is assumed to be an emergent function of affordances, social learning, individual learning and habituation, personal states, and niche construction (see Figure 1 and Table 1). In our model, agents move in a landscape of affordances where they encounter either pro-environmental or non-environmental affordances and act upon them (i.e., behave pro- or non-environmentally; see Figure S17). Behaviors then lead to the development of habits, social transmission (learning or copying behaviors from others), and the modification of the landscape of affordances (i.e., cultural niche construction). In particular, we show how the composition of affordances in a socio-ecological system, such as infrastructures that afford pro-environmental behaviors, plays an essential role in shaping collective behavioral patterns. Our model illustrates how even linear increases in pro-environmental affordances can lead to the non-linear adoption of collective pro-environmental behavioral patterns. We refer the reader to the Experimental Procedures for a thorough description of our model and its multidisciplinary theoretical assumptions.

We proceed by first presenting an abstract version of the model with parameter values set as defined in Table S3. These

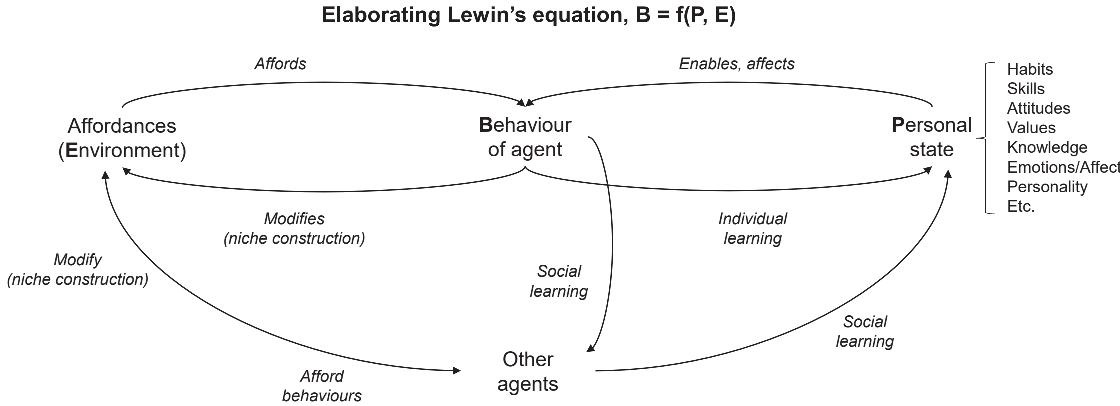

Figure 1. Conceptual Model
Elaboration on Lewin's equation. The figure implements several known feedback loops. The couplings form a socio-ecological system of human behavior.

are arbitrary parameter values; most parameter values are set at around halfway through the feasible parameter range, except that the rates of social learning and individual learning are set to values that reproduce macro-level output similarly to known social-learning patterns (i.e., S-shaped curves[11,45]). The rate of social learning is set slightly higher than that of individual learning (see Social Learning and Networks). Section Abstract Model Run thus demonstrates the general characteristics and mechanisms of the model by using abstract parameter values. In particular, the abstract version of the model aids in understanding the leverage points of the simulated system. We refer the reader to the Experimental Procedures for a description of the ABM and to the ODD Protocol and Sensitivity Analysis subsections (Figures S7–S16) of the Supplemental Experimental Procedures for a more complete picture of how each parameter affects the outcome of the model. See Table S2 for a list and definition of the model's parameters.

We then continue with empirical validation by fitting the parameter values to reproduce real-world macro-level patterns. We use the cultural evolution of cycling behaviors in Copenhagen as a case study. This empirical validation is intended to ensure "that the model generates data that can be demonstrated to correspond to similar patterns of data in the real world."[16]

Abstract Model Run

We run the model for 2,000 timesteps by measuring the variables of interest (pro-environmental and non-environmental behaviors) at the end of the model run (Figures 2 and 3) or producing time-series data by following pro-environmental and non-environmental behaviors at each timestep (Figure 4). We chose 2,000 timesteps as the arbitrary end of this model run given that this allows for considerable changes in behavior with the chosen parameter values (Table S3).

Figures 2A and 2B illustrate the end results of the model at timestep 2,000. Here, the initial proportion of pro-environmental affordances is varied from 0 to 1 with intervals of 0.01 and 30 simulation runs for each pro-amount value. This produces a total of 3,030 simulation runs. To illustrate the effects of niche construction (i.e., behavior altering the environment), Figure 2A plots the results with both rates of niche construction set at 10 (which corresponds to a 3% chance of niche construction following any behavior), and Figure 2B plots the results without any niche construction.

We can immediately notice that the system produces a tipping point, or a phase transition, when the initial proportion of pro-environmental affordances is around 0.5. When the initial proportion of pro-environmental affordances is above 0.5, the proportion of pro-environmental behaviors at the end of the model run increases drastically and vice versa. It is quite intuitive to understand why this happens. When the affordances in the environment bias the agents to behave in some way, this behavior becomes more probable than the alternative. Because of social learning and habituation, this bias in afforded behavior diffuses through the social network, altering personal states of the agents, modifying the environment through niche construction, and thus triggering a positive-feedback loop. A linear increase in affordances will have non-linear effects on the uptake of pro-environmental behaviors.

This produces an S-shaped curve, where the initial composition of affordances has a non-linear effect on the outcome of environmental behaviors (Figures 2A and 2B). Figure 3 produces k-means clusters of the pro-environmental behaviors of Figure 2A. The cluster analysis illustrates how drastic the phase transition from low to high proportions of pro-environmental behavior is when the initial composition of affordances is altered. The ellipses in Figure 3 contain roughly 95% of all data points.

Using global sensitivity analysis, Figure S15 illustrates how robust this tipping point is. Here, 300 near-random samples of parameter values are simulated (via Latin hypercube sampling[46]), whereby each is run five times with varying random seeds. Figure S15 thus illustrates that even when other parameters are allowed to vary freely (within a predefined range; see Table S1), the tipping point will emerge. This illustrates that in the system of social behavior, the non-linear effect of affordances on behavioral patterns is robust.

Notice that the same cannot necessarily be said of the effect of initial personal states on behavioral outcomes (Figure S16). For instance, the red box in the lower right corner of Figure S16 highlights cases where the agents, despite initially having high pro-environmental personal states, were mainly behaving non-environmentally at the end of the model run. This is most likely due to a lack of pro-environmental affordances, as well as the

Table 1. Model Assumptions

Description	Causality	Theories and Evidence (Non-exhaustive)
Ecological information specifies a variety of opportunities for behavior, or "affordances"	$E \rightarrow B$	ecological psychology and affordance theory,[1,4,34,35] behavior field theory,[35] and design theories[36]
Personal states affect behavior	$P \rightarrow B$	theory of planned behavior,[7] habituation,[37] and capability approach[38]
Behavior modulates personal states	$B \rightarrow P$	habituation,[37] individual (or asocial) learning,[11,39] cognitive dissonance and self-justification,[5,40,41] and the foot-in-the-door effect[40]
Behavior shapes the environment	$B \rightarrow E$	niche construction and cultural niche construction[9,10] and cumulative cultural evolution[42]
Behavior occurs in a social network with social learning, transmission, and cognition	$B_{(self)} \rightarrow P_{(others)}$, $B_{(others)} \rightarrow P_{(self)}$	social learning,[10,11,39] social cognition,[43] spread of innovation in social networks,[44] group conformity and social norms,[45] and cumulative cultural evolution[42]

This table elaborates on Lewin's equation (Equation 1), where behavior (B) is a function of person (P) and environment (E).

interference of other personal states on behavior. This is somewhat analogous to the attitude-action gap observed in environmental behavior.[2,47] Pro-environmental personal states do not translate into pro-environmental behavior if there are no opportunities to do so, and environmental design might prove to be a more reliable leverage point into pro-environmental behavioral change than attempts at altering personal states.[2]

Figure 4 plots time-series data with the parameter values specified in Table S3. Figures 4A and 4B plot the development of pro-environmental behaviors when initial pro-environmental affordances compose 50% of the affordance landscape. A total of 300 simulations were run for each plot. Figure 4A plots the data with niche construction, and Figure 4B plots them without niche construction. With both plots, the mean proportion of pro-environmental behavior remains stable over the model run. However, notice how the standard deviations (shaded area) increase with niche construction.

In Figures 4C and 4D the initial composition of pro-environmental affordances is altered to 60%. The minor (10%) change in the landscape of affordances has a drastic non-linear effect on the adoption of pro-environmental behaviors. As described above, this self-reinforcing process is mainly a product of social learning and habituation induced by the alteration of the affordance landscape.

Notice also how the curve in Figure 4C (with niche construction) is steeper than the curve in Figure 4D. Increases in niche construction rates seem to hasten the self-reinforcing effect on the adoption of behaviors.

Empirical Validation

Empirical validation (Figure 5), or testing that data produced by an ABM correspond to "empirical data derived from the real-world phenomenon," is an important step in modeling.[16] However, a common challenge with empirical validation is that "inputs and outputs in 'the real world' are often poorly defined or nebulous."[16] We acknowledge that this is the case with some parameters of the present model: finding reliable empirically grounded values for parameters such as the rates of social learning, individual learning, and niche construction is difficult if not impossible (see Discussion). However, regardless of this important caveat, we maintain that illustrating that the model can produce macro-level patterns resemblant of real-world data, with reasonable assumptions (see Experimental Procedures), is an important step in assessing the validity of the model.

We use the case of bicycling and driving habits in the city center of Copenhagen as a case study. Particularly since the 1990s, Copenhagen has seen a rapid increase in the proportion of cyclists. This change in transport habits has earned Copenhagen the title "City of Cyclists."[48] This change has not come for free, and it has been attributed not only to the emergence of a cycling culture but also to heavy investment into cycling infrastructure, such as cycling tracks, bridges, and a public bicycle scheme introduced in 1995.[48–50] Overall, Copenhagen has witnessed a considerable increase in affordances for cycling: people are increasingly satisfied with Copenhagen as a cycling city and with bicycle parking opportunities, and the amount of cycling tracks has increased considerably since the 1990s (Figure 6A).[49] There have also been decreasing amounts of seriously injured or killed cyclists, and in 2018, 77% of Copenhageners stated that they felt safe while cycling in traffic.[49]

We use the case of cycling in Copenhagen to illustrate how our model can produce realistic macro-level patterns of the evolution of pro-environmental behavior (cycling) and non-environmental behavior (driving). Although, as noted, parametrization is difficult, we know from available data that in 1970 driving was about four times more common than bicycling, and in 2018 the number of cyclists seemed close to overtaking the number of drivers (Figure 5A; data acquired from the City of Copenhagen through personal communication). The development of cycling also seems to resemble a cumulative distribution curve, which could indicate a strong presence of social learning (which is entirely expected of a human society; see Social Learning and Networks). We also know that affordances for cycling in Copenhagen have increased nearly linearly over time (see Figure 6A) and that the policy emphasis has been on constructing the environment to be cycle friendly.[49,50]

Using a genetic algorithm and manual tuning, we set the initial parameter values of the model as described in Table S4. We take one timestep of the model to represent 1 day and set the total model run to span 56 years or 20,440 timesteps (by assuming 365-day years). Although the model spans 56 years, it involves only one generation of agents. This is a simplifying modeling

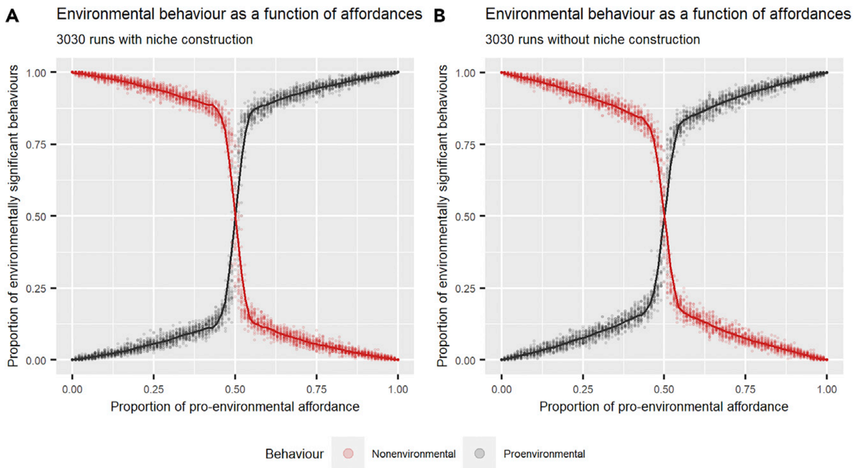

Figure 2. Pro- and Non-environmental Behavior as a Function of Initial Affordances

Results at the end of the model run from a total of 3,030 simulations (for each plot) with varying random seeds. The lines are smoothed conditional means or LOESS (locally estimated scatterplot smoothing) regressions with (A) niche construction and (B) without. Notice how the curves of (A) are steeper than those of (B): niche construction can amplify the positive-feedback loop.

choice that allows us not to deal with the thorny issue of how cycling behaviors (or personal states) would be inherited through generations. However, the model does include random mutations of personal states, which could be interpreted to simulate the random effects of intergenerational knowledge transfer (vertical cultural transmission).

Figure 5B presents the results of 300 runs of the simulation. As in real-world data (Figure 5A), at timestep 1 of the model run, the proportion of cyclists is roughly one-fourth of the proportion of drivers. However, as a result of feedback loops among pro-environmental niche construction, social learning, and individual learning, the proportion of cyclists rises at an accelerating rate, eventually almost overtaking the number of vehicle drivers by the year 2018 (or timestep 17,885). Although there is considerable variance between the model runs, the mean numbers of cyclists and drivers seem markedly similar to real-world patterns from Copenhagen, even when the model is left unsupervised after initial configuration (as is done with each run).

To illustrate what a single model run might look like, we manually selected a representative model run, illustrated in Figure 5C. Note, however, that many of the 300 model runs will see either a faster or slower adoption of cycling and driving habits (as indicated in Figure 5B). We allowed the simulations of Figure 5B to project to the future, illustrating an ever-increasing number of cyclists. However, we caution that this is not a prediction for the development real-world patterns in Copenhagen because obviously other major factors (many of which are inherently unpredictable) might influence or hinder this development. For instance, it has been speculated that the extension of the metro line in Copenhagen might reduce the number of daily cyclists.

Figure 5D depicts one factor that triggers the tipping point in the Copenhagen simulation: the rate of pro-environmental niche construction. It could be interpreted as suggesting that if the city had invested less into the development of cycling infrastructure, the accelerating rate of cyclists witnessed in the real-world data might not have taken off nearly at the rate that it did. That is, the composition of affordances over time, even if the development of affordances is close to linear (see Figure 6A for real-world data and Figure 6B for simulated data), can have non-linear self-reinforcing effects on the adoption of cycling behaviors.

DISCUSSION

If the assumptions of our model hold and systems of human behavior portray all five feedback processes defined in the Introduction and Experimental Procedures, our model gives further evidence for locating leverage points for collective pro-environmental behavioral change.

In particular, our model illustrates how (even minor) changes in the landscape of affordances can trigger non-linear (S-shaped) changes in collective behavioral patterns as a result of increased action opportunities, habituation, and social learning. This S-shape, or cumulative distribution curve, is known to signify social-learning patterns: "Hundreds of studies conducted by sociologists have repeatedly found that the spread of new technologies, practices, and beliefs follows an S-shaped cumulative distribution curve."[45]

Giving people increased opportunities to behave pro-environmentally can trigger a self-reinforcing feedback loop (recall Figure 1). Here, an increase in pro-environmental affordances leads to increased pro-environmental behavior, whereby people develop stronger pro-environmental habits, which in turn leads to social learning and transmission of behaviors through social networks, which might result in increased pro-environmental niche construction (i.e., construction of pro-environmental affordances), eventually reinforcing any existing habits and so on.

As illustrated by the case presented in our empirical validation, a responsive government can greatly facilitate this process. Designing urban environments to facilitate pro-environmental behavior patterns can play a central part in triggering tipping points in the adoption of pro-environmental behaviors, as has arguably been the case with the evolution of cycling cultures in Copenhagen (see Figures 5 and 6). Furthermore, our results suggest that as a result of potential tipping points, the design of urban environments to facilitate pro-environmental behaviors should continue even if the effects (i.e., adoption of pro-environmental behaviors) are not initially obvious. This is because it might only be after a certain threshold of affordances that the accelerating adoption of behaviors takes place (Figure 2).

Because other potential leverage points, such as changes in personal states, are less robust (Figure S16), our model suggests that tipping points in collective pro-environmental behaviors might be most efficiently triggered by changes in the physical form of environments. This is an interesting result because it is arguably also the physical environment that urban designers, policy makers, and other decision makers have most control

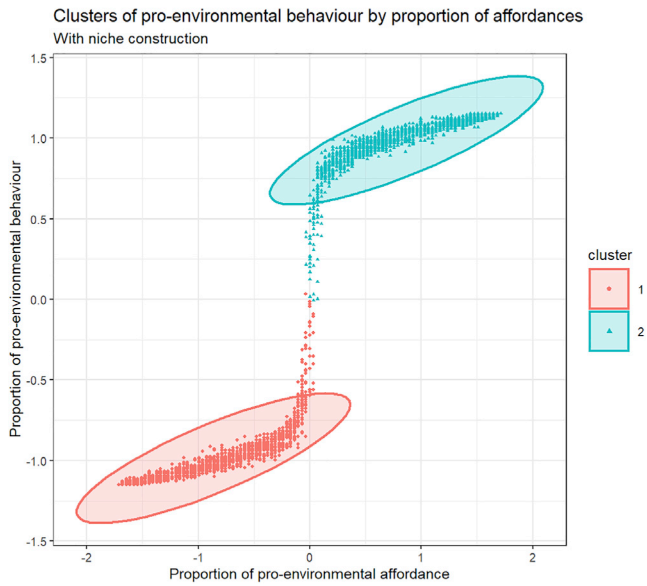

Figure 3. The Phase Transition

A k-means cluster plot of the pro-environmental behaviors of Figure 2A. Ellipses contain roughly 95% of all data points. The axes are standardized (standard deviations from the mean).

over, and leveraging environmentally significant behaviors by means of communication or information campaigning has proved to be notoriously difficult.[2,51,52] Perhaps a more reasonable information-oriented approach to collective behavioral change would be through the redesign of "general ecological information"[34] or the information in our everyday environments that specify the affordances within our niche (see Environment Affords Behavior). Through habituation, social learning, and social transmission of behaviors, the form of the physical environment can have more definitive, long-lasting, and widespread effects on our behavior than might generally be assumed.

The results also highlight the role of cultural niche construction in sustainability transitions. Whereas urban theorists such as Christopher Alexander[53] and Jane Jacobs[54] have for long noted the importance of self-organizing communities in the development of lively and resilient cities, our model shows how increasing the capacity of a society to construct its own niche can hasten the adoption of pro-environmental behaviors. Thus, letting communities evolve and self-organize can result in self-reinforcing sustainable behavioral patterns if such a community has pro-environmental personal states (note, however, that the converse is true if the community does not have pro-environmental personal states).

Overall, our model gives further justification for investment into the design of pro-environmental affordances. This is important given that many cities are currently considering investment into infrastructures that facilitate pro-environmental behavior. Our model suggests that making pro-environmental behavior as easy as possible, the default option for behavior, and the path of least resistance might have long-lasting and non-linear effects on the adoption of pro-environmental habits and effectively trigger tipping points in the sustainable cultural evolution of a social system.

Because of the large number of interconnected processes, each aspect of the present model was intentionally kept at a moderate level of complexity. This, we argue, keeps the model in the so-called "Medawar zone"[17] of complexity: not too simple (and thus neglecting essential mechanisms of the modeled system) but not too complex (and so becoming cumbersome and "bogged down in detail"). However, the model is open for further development and additions of more complex layers. These could, for instance, include more elaborate psychological decision-making processes (including social cooperation or competition[21]) and a higher variety of affordances and behaviors.

However, as we have stated above and as has been discussed by many others,[55–57] social scientific, cognitive, and psychological theories often do not provide enough detail to unambiguously specify algorithms to implement them. Even the same theories can produce different modeling outcomes as a result of variability in model architecture, choice of (numerical) representations, and empirical data or goals of the modeler, and minor differences in decision making can be amplified in the interactions of thousands of agents.[56,57] As is generally the case with complex systems, small changes in initial conditions can cause large variance in emergent end results.[57,58]

Moreover, social and psychological theories might altogether lack formal descriptions of mechanisms essential for modeling.[55] In the case of our model, precisely defining parameters such as the rate of niche construction poses particular challenges—not the least because complexity scientists such as Stuart Kauffman have suggested that the creative processes through which human cultures alter their material and technological world are fundamentally unpredictable and indescribable by law-like algorithms.[59] We acknowledge the need, where possible, for collaboration in the development of formal structures for implementing social scientific and psychological theories for ABMs, including systematic comparisons of models,[55] and believe the present model could be refined in particular through such interdisciplinary collaboration.

The model is also easily modified to include interactive elements, such as "policy buttons," which could trigger discrete changes in the landscape of affordances and personal states. This could, we imagine, also be used for educational purposes or co-creation with, e.g., policy makers or urban designers. We also acknowledge that the model could be further developed by the inclusion of other forms of empirical data, such as psychological data measured with surveys or geographical data[60] (or indeed both, e.g., with PPGIS[61] approaches).

Conclusion

In conclusion, our ABM illustrates how changes in the composition of affordances (action opportunities) in our everyday environments can trigger tipping points in the collective adoption of pro-environmental behaviors. Even near-linear increases in pro-environmental affordances can trigger the non-linear, self-reinforcing adoption of pro-environmental behaviors. These feedback loops emerge from the interconnected processes of habituation, social learning, and niche construction. We interpret this as giving further justification for the design and funding of everyday environments where the affordances for pro-environmental behavior are knowingly increased and thus make pro-environmental behavior the path of least resistance.

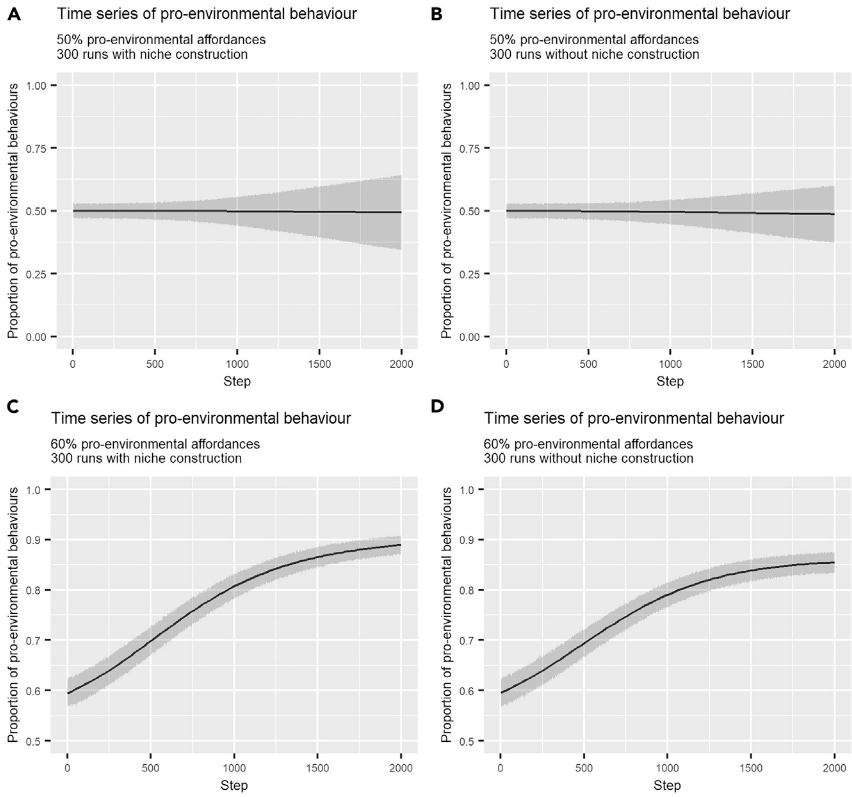

Figure 4. Time-Series Data

Mean time-series data of 300 model runs (for each plot) track the proportion of pro-environmental behavior over time. In (A) and (B), initial pro-environmental affordances are set at 50%. In (C) and (D), initial pro-environmental affordances are set at 60%. Niche construction is shown in (A) and (C) but not in (B) or (D). Shaded areas signify ±1 standard deviation. Lines are smoothed conditional means (generalized additive model [GAM]).

EXPERIMENTAL PROCEDURES

Model Assumptions

> In psychology one can begin to describe the whole situation [from which behavior emerges] by roughly distinguishing the person (*P*) and his environment (*E*). Every psychological event depends upon the state of the person and at the same time on the environment, although their relative importance is different in different cases. Thus we can state our formula [...] as $B = f(P, E)$. [...] Every scientific psychology must take into account whole situations, i.e., the state of both person and environment. This implies that it is necessary to find methods of representing person and environment in common terms as parts of one situation.[32]

The design of the model presented in the present paper expands on Kurt Lewin's equation (Equation 1).[32] Therefore, it proposes a systems approach to studying the emergence of behaviors by suggesting that, to explain behavior, we must account for the whole situations from which behaviors emerge.

Although it is a useful heuristic, Lewin's conceptual model alone does not provide enough detail for designing a reproducible formal computational model. Therefore, our model draws on a variety of fields, ranging from evolutionary ecology to cultural evolution to (social) psychology and cognitive science, to introduce various levels of detail to Lewin's equation. Namely, our model elaborates Lewin's model from a complex and dynamical systems perspective, where the cultural evolution of behavior within a society is understood as a product of several interconnected feedback loops. Thus, our model adds several causal links to elaborate on Lewin's formula (Table 1).

This model design is influenced by dynamical systems approaches to cognition and behavior.[3,31] That is, its focus is on studying how the human-environment system evolves *over time* and *as a whole* given ranges of initial conditions. According to Chemero[3] and Lewin,[32] the model assumes that focusing on only one of either personal states or the environment in insufficient for describing the emergence of behavior:

> Dynamical systems theory is especially appropriate for explaining cognition as interaction with the environment because single dynamical systems can have parameters on each side of the skin. That is, we might explain the behavior of the agent in its environment over time as coupled dynamical systems [...] It is only for convenience (and from habit) that we think of the organism and environment as separate; in fact, they are best thought of as forming just one nondecomposable system.[3]

Dynamical systems approaches to human behavior are readily available in the fields of ecological psychology[1,3,35] and (radical) embodied cognitive science.[3] Moreover, dynamical systems approaches to studying or modeling systemic change[12] and coupled human-nature systems[60] have been recently proposed in the context of socio-ecological systems theories. However, ecological psychology and cognitive science in particular have traditionally struggled with taking into account the social dimension.[62] To remedy this, the present article also models the dynamical human-environment system as a social one: no behavior is truly private in a socially connected world where organisms teach, copy, learn in social networks, and modulate their niche to shape its affordances.[10] The conceptual model underlying the ABM is illustrated in Figure 1. In the following sections, the theoretical and methodological assumptions of this model are elaborated (see Table 1 for a summary). For a more detailed conceptual model, see Kaaronen.[2]

Environment Affords Behavior

For any active organism, the environment affords a variety of behaviors. In ecological psychology, these opportunities for action have traditionally been called ''affordances.''[1,3,35] Affordances are commonly defined as the relations between the abilities of animals to perceive and act and features of the environment.[3,63] That is, an affordance is the functional meaning of an environment for an organism. A chair, for instance, affords the function of sitting for humans, whereas a bicycle affords cycling. Affordances are specified to an organism through the availability of ecological information.[1] Ecological information is ''the set of structures and regularities in the environment,'' such as patterns of light or sound reflected by the physical environment, ''that allow an animal to engage with affordances.''[34]

It is important to emphasize that an affordance is a relational construct, or a relation between capabilities and the environment.[3] For instance, a bicycle path will only afford bicycling for a person who knows how to cycle. The basic logical structure of an affordance can therefore be defined as ''affords-ϕ (environment, organism), where ϕ is a behaviour.''[63]

Ecological psychologists have thus focused on the functional meaning of environments for animals, particularly humans. A central tenet of ecological psychology is that in our immediate experiential and phenomenological world, we do not generally perceive our environment as functionally meaningless. For instance, when we perceive a chair, we do not merely perceive

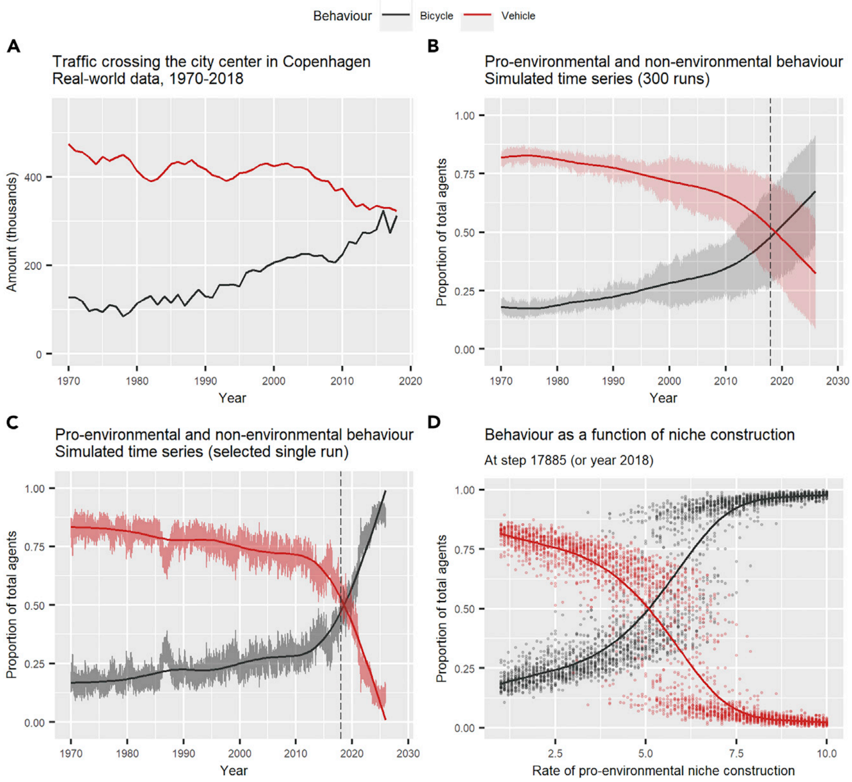

Figure 5. Empirical Validation

Real-world and simulated data of cycling and driving patterns in Copenhagen. Shown are (A) real-world data from 1970 to 2018 and (B and C) simulated time-series data, the latter of which have a dashed vertical line at the year 2018. 300 simulation runs with a ribbon of ±1 standard deviation are shown in (B), and a single representative simulation run, manually selected from (B), is shown in (C). Results at year 2018 (timestep 17,885) when the rate of niche construction is varied are illustrated in (D). Lines in (B)–(D) are smoothed conditional means (GAM). In (D), notice the phase transition between niche construction rates of roughly 5 and 7, similar in logic to the tipping point illustrated in Figures 2A and 2B.

a static object; rather, we perceive an opportunity for sitting.[64] In other words, (some of) the primary things we perceive are affordances.[1]

Rietveld and Kiverstein[4] have argued that humans inhabit a particularly rich and resourceful "landscape of affordances." That is, we have designed and fitted our environments—urban environments in particular—with a large variety of opportunities for action. This notion of a landscape of affordances is crucial for the present model given that the model's grid (Figure S17) effectively represents a landscape of affordances.

Recently, affordance theory has been applied particularly in assessing the functional meaning of urban form, e.g., the provision of sustainable affordances in urban environments[2,65] and the child friendliness of affordances in urban and rural environments,[14] and it has also found foothold in sense-of-place research.[66] What these approaches have in common is the attempt to study or model the psychologically meaningful dimensions of the material environment and the influence of the physical environment on human behavior.[67]

Moreover, research in ecological and environmental psychology has suggested that a "positive interaction cycle" could emerge between humans and environments when affordances are readily available.[14] That is, an increase in affordances for behavior B will increase the probability of actualizing behavior B, which in turn increases the probability for engaging with affordances for behavior B in the future (as a result of increased motivation, learning, habituation, and other factors; see Behavior Modulates Personal States). Similar feedback loops have been proposed by Chemero[3] and Kaaronen.[2]

Behavior Modulates Personal States

The ways in which we behave—or whatever affordances we act upon—often influence how we behave in the future. This is because humans learn from individual behavior (individual or asocial learning), form habits, and have a tendency to adjust their attitudes and values to their behavior, among an innumerable variety of other cognitive, psychological, and neural factors.

A habit is an automatic behavioral response to environmental cues and is believed to develop through the repetition of behavior in consistent contexts.[6] Particularly with commonly encountered cues (or affordances), a habit leads to the frequent performance of a behavior B, and habits are often strong enough to override any conscious or intentional regulations for that behavior.[6] We have a tendency to behave in the ways in which we are used to behaving or the ways in which our environment prompts us to behave, sometimes even regardless of our intentions or desires. In everyday life, this is almost self-evident: our behavioral patterns are far from random, and to give some examples, we often shop for the same items as we have shopped for before, use familiar routes and modes of transport, and so on. The process of gaining habits, or a "behavioral response decrement that results from repeated stimulation," is called habituation.[37]

Other fields of (social) psychology and cognitive science have illustrated how we have a tendency to modulate our internal states (such as attitudes and values) to our behavior. For instance, research in cognitive dissonance theory illustrates how through processes of self-justification, we have a tendency to adjust our attitudes and beliefs to conform with our current, past, or recent behavior.[5,40,68] More recent approaches to cognitive science, such as predictive processing, also support the notion that we have a tendency to adjust our internal models of the world to minimize prediction error or to keep our internal models of the world in tune with our past and current behavior.[68,69] If these internal states are predictors of behavior B (see Personal States Affect Behavior), this would also imply (all other things being equal, and on average) that behavior B would increase the future probability of behaving in that way.

Moreover, behavior can result in a wide variety of individual learning.[11,39] This is fairly uncontroversial: if a person enacts behavior B (e.g., cycling) regularly, they might improve their cycling skills and thus engage in that behavior more often in the future. For instance, Kyttä[14] has suggested that repeated engagement with familiar affordances can result in increased motivation to interact with them in the future.

Thus, crudely, it could be asserted that on average and in the long run (and all other things being equal), behaving in a way B at time t would increase the probability of performing behavior B at time t_{+1}, mediated through changes in the personal state P (which include individual learning and habituation, among other cognitive processes).

Personal States Affect Behavior

The notion that the personal state of a human has an effect on behavior is perhaps the most familiar assumption of the present model. We like to think of our behavior as being guided by our attitudes, values, subjective norms, and so on. Indeed, a branch of psychology dealing with the "theory of

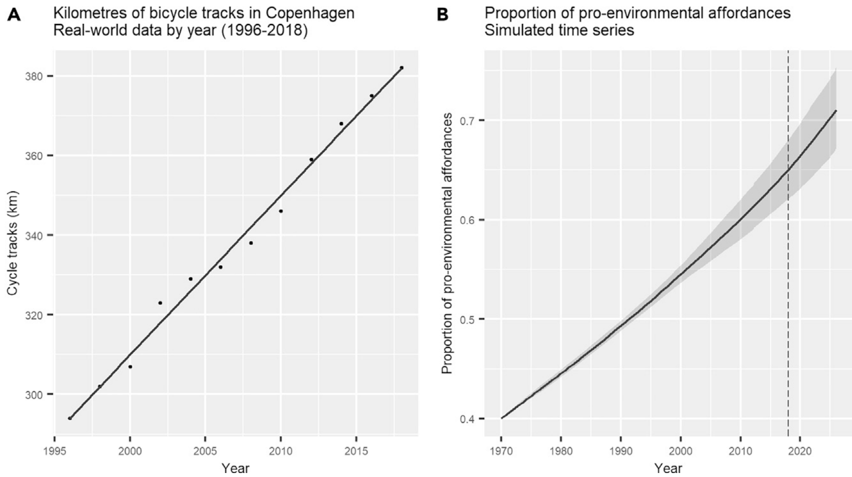

Figure 6. Development of Bicycling Affordances in Copenhagen

(A) Real-world data of kilometers of bicycle tracks in Copenhagen from 1996 to 2018 with a linear regression fit for illustrative purposes.

(B) The proportion of pro-environmental affordances over time in 300 simulation runs with smoothed conditional mean (GAM). The shaded area signifies ±1 standard deviation, and the vertical dashed line is at year 2018.

planned behavior" deals explicitly with this;[7] it proposes that behavior can be predicted from "attitudes toward the behavior, subjective norms [an individual's perception about a behavior], and perceived behavioral control."[7]

However, there exist a wealth of behavioral patterns that are not predicted by attitudes or subjective norms. This has been studied extensively in the context of the attitude-action gap.[47,70] For instance, possession of environmental knowledge and environmental awareness does not necessarily translate into pro-environmental behavioral patterns.[47,71] This discrepancy might be a result of old habits or, simply, the lack of given and easily accessible action opportunities or affordances.[2]

For these reasons, in the present text, the personal state (*P*) of an organism is defined as the totality of an organism's properties that dispose it to behaving in a particular way. More precisely, in the present model, the *P* of an agent corresponds to the probability of interacting with a certain type of affordance. Therefore, the personal state as referred to in this paper is much more than just a conception of attitudes, subjective norms, or values—it is an umbrella term that also includes adopted habits (even unconscious ones), personality, learned sensorimotor skills, (tacit and explicit) knowledge, capabilities,[38] and so on.

Behavior Shapes the Environment

Not only do affordances influence human behavior, but we also actively shape the affordances within our ecological niche. This process, "whereby organisms, through their activities and choices, modify their own and each other's niches," is called niche construction.[8] Although the roots of niche construction theory lie in evolutionary ecology,[9] niche construction theory has more recently gained interest in cognitive science[3,69,72] and cultural evolution.[8,10] For present purposes, it suffices to understand niche construction as the construction of non-random biases on behavioral selection pressures.[9]

Through the process of niche construction, we design our environment to afford a large variety of behaviors that reinforce our daily habits and routines.[69] Recent theories in cognitive science suggest that, in general, niche construction occurs to make the environment more predictable—that is, we tend to design our environment so that it conforms to our cognitive models.[69,73] As Veissière et al. argue,[74] niche construction "can be viewed as the process whereby agents make their niche conform to their expectations" (see also Constant et al.[72]). Thus, the behavioral selection pressures caused by niche construction would then generally serve to reinforce past behaviors.

In the context of the present model, niche construction could include urban design (e.g., implementation of bicycle paths as a response to increased demand), household design (e.g., fitting one's household with eco-friendly affordances, such as recycling bins), or other forms of self-organizing social activities (e.g., providing a community with more autonomy in designing their niche from the bottom up; see Alexander[53]).

Social Learning and Networks

Any description of human behavior that does not account for social learning and transmission would be radically incomplete. Therefore, in the present model, all behavior is assumed to emerge in a social network. This is because humans are, above all, social learners, and our social capabilities are arguably the feature that sets us most apart from other species.[10,75]

Social learning is the process through which learning is "facilitated by observation of, or interaction with, another individual or its products."[11] In a social network, behaviors and information spreads through a process known as social transmission, where "the prior acquisition of a behavioral trait T by one individual A, when expressed either directly in the performance of T or in some other behavior associated with T, exerts a *lasting positive causal influence* [emphasis added] on the rate at which another individual B acquires and/or performs T."[11]

Social learning and social transmission form a cornerstone of studies of cultural evolution.[10,11] This is simply because "much behavioral variation between societies can be explained in terms of cultural transmission: people acquire knowledge, customs, attitudes, values, and so on from other members of their society."[45] In fact, the social intelligence hypothesis[76] goes as far as to propose that, particularly in the case of humans, social learning is more common and influential than individual learning.

For the purpose of this model, this implies that whenever an agent engages with an affordance and behaves successfully, it will exert lasting positive causal influence on its local social network, increasing their probability to behave similarly.

Model Design

Concluding from the previous sections, we can now define Lewin's equation's parameters more precisely (see Table 1). Behavior is a function of person and environment (Equation 1), where, first, the environment (*E*) is a landscape of affordances consisting of a distribution of opportunities for behavior. Second, behavior (*B*) at time *t* occurs from successful interaction with affordances (*E*) and can lead to non-random modification of the environment (*E*), altering the selection pressures for behavior at t_{+1}. Third, a personal state (*P*) corresponds to the probability of engaging with an affordance and is modulated by behavior (*B*). Fourth, all behavior (*B*) occurs in a social network where behaviors affect the personal states (*P*) and thus behaviors of others.

Although by no means exhaustive, this conception provides a coherent framework for designing a formal model around Lewin's equation. We now proceed to a description of the ABM itself. A more detailed description of the model's procedures and mechanisms can be found in the ODD Protocol subsection of the Supplemental Experimental Procedures. The ODD Protocol also includes Unified Modeling Language diagrams (Figures S1, S5, and S6) and further elaboration of network structure (Figures S2–S4).

In the spirit of pattern-oriented modeling,[17] we rely on "multiple patterns observed in real systems to guide design of model structure." We have designed the model in accordance with multiple micro-level patterns, from which realistic macro-level patterns emerge.

The subsection Sensitivity Analysis in the Supplemental Experimental Procedures also includes two kinds of sensitivity analyses: local one-factor-at-a-time (OFAT) sensitivity tests,[77] where the model's sensitivity to each parameter is analyzed individually (Figures S7–S13), and global sensitivity tests (Figures S14–S16), where all free parameters are allowed to vary with the use of Latin hypercube sampling.

Model Setup

Affordances

The grid of this model represents a landscape of affordances.[4] This model has two types of affordances: a pro-environmental affordance, where pro-environmental "refers to behavior that harms the environment as little as possible, or even benefits the environment,"[78] and a non-environmental affordance, where non-environmental refers to an environmentally harmful activity.

In its abstract form, the model is indifferent to what these affordances precisely are. What is important for the model design, however, is that these behaviors are dependent. For instance, if the pro-environmental affordance is understood to represent an opportunity for "cycling," engaging with this affordance should have an effect on the probability of engaging with the non-environmental affordance (e.g., "driving"). The abstract categorization into binary affordances (non-environmental and pro-environmental) is not a necessity for the model design, but it makes for more simple interpretation. Considering that modeling the whole of the landscape of affordances in any given human niche would be practically impossible, this limitation is also a pragmatic one.

The model represents affordances as patches within NetLogo's Cartesian grid. See Table S2 for a brief definition of the model's parameters and the Discussion for thoughts on how the model could be extended to include more behaviors in the future. The model's setup procedure generates a landscape of affordances, where the initial proportion of pro-environmental affordances is assigned by the parameter "pro-amount."

Networks

In model setup, agents are spawned on the grid at random locations (the default value for the "number-of-agents" is 300). During the generation of agents, links are generated to connect the agents, creating a Klemm-Eguíluz network.[79] The Klemm-Eguíluz model was chosen because it represents two characteristics we know to characterize social systems: societies have hubs (the network degree distribution follows a power law distribution, i.e., it has scale-free properties), and societies have highly clustered local communities (social networks have high clustering coefficients).[79] Although our ABM also supports the Erdős-Rényi model[80] (random network), the Barabási-Albert model[81] (scale-free network with low clustering), and the Watts-Strogatz small-world model[82] (highly clustered network without scale-free properties), the Klemm-Eguíluz model was chosen because it combines the best aspects of the latter two models: scale-free properties and high clustering. The code for creating the Klemm-Eguíluz model was adapted with permission from Caparrini's[83] Complex Networks Toolbox. All links in this model are undirected such that information flows both ways.

The model is quite robust against variation in network density, although extreme values will create more polarized outcomes in model behavior. In the following simulations, we set the Klemm-Eguíluz model parameter μ to 0.9 and $m0$ to 5 (see Caparrini[83] for a concise definition of these parameters and Klemm and Eguíluz[79] for a more detailed account). This creates a network with a long-tailed degree distribution and a high global clustering coefficient. With these parameter values, the model relatively rarely creates agents with more than 150 direct connections. Although it is notoriously difficult to operationalize a realistic network density, the chosen network structure does respect the suggested upper cognitive limit of the degree of stable social relationships, or Dunbar's number,[84] which suggests that humans are cognitively incapable of maintaining over 150 social relationships.

Personal States

Each agent is assigned two initial personal states, "pro-env" and "non-env." The former defines the probability of interacting with a pro-environmental affordance, and the latter defines the probability of interacting with a non-environmental affordance. Personal states are initially sampled from a normal distribution with a mean defined by the parameters "initial-pro" (for pro-env) and "initial-non" (for non-env) and a standard deviation of 0.15. A standard deviation of 0.15 (in the range of 0–1) is roughly in line with data on standard deviations of environmental attitudes and self-reported behaviors. For instance, Chan[85] reports standard deviations ranging from 0.75 to 0.8 for self-reported pro-environmental behaviors on a five-point scale.

Because personal states are probabilities, they are bounded within the range [0, 1]. Each agent is given individual upper bounds and lower bounds for their personal states. The bounds are drawn from normal distributions with means of 0.2 (lower) and 0.8 (upper) and a standard deviation of 0.05. This allows for some agents to adopt more extreme habits than others, which is in line with empirical observations; for instance, some people might be more prone to adopting strict vegan habits than others who adopt, at most, part-time vegetarian or flexitarian eating habits. Note that the personal states need not add up to 1; it is possible, for example, that a person would actualize the affordance of driving (when encountering a driving affordance) with a probability of 0.55 while also actualizing an encountered cycling affordance with a probability of 0.55.

Model Processes

Overview

The Go command launches the model. Agents move in a random walk around the landscape of affordances. During each tick (timestep), the agents have a chance of interacting with the affordance (patch) they are currently on. For example, if an agent is on a pro-environmental affordance and currently has a pro-env value of 0.5, it has a 50% chance of interacting with that affordance. Each agent must behave somehow during each tick. Therefore, if an agent does not interact with an affordance successfully, it will move one step forward and try again by repeating this procedure until it interacts successfully with an affordance it encounters. Successfully interacting with an affordance represents one instance of behavior. Behaviors are tracked through the global variables "pro-behavior" and "non-behavior," which are reset at the beginning of each tick. This allows us to track the total amount of pro-environmental and non-environmental behaviors at the end of each timestep.

Individual Learning

Successful behavior launches a series of procedures. First, behaving leads to individual learning and habituation. If, for instance, an agent behaves pro-environmentally at time t, it will set its personal state pro-env to "pro-env$_{(t)}$ + asocial-learning" and its non-env to "non-env$_{(t)}$ $-$ asocial-learning," where "asocial-learning" is the rate of individual learning and habituation. The sequence is identical for non-environmental behavior. It is important that an increase in pro-env leads to a decrease in non-env (i.e., they are not independent) because otherwise the model would practically always converge to a state where each agent possesses a maximum possible value for both pro-env and non-env. The decrease can simply be understood as the decay of an acquired habit when a given behavior is not practiced.

Social Learning

Second, behavior leads to social learning and transmission. If an agent behaves non-environmentally at time t, it will ask its network neighbors (the agents it is directly linked to) to set their non-env to "non-env$_{(t)}$ + social-learning" and its pro-env to "pro-env$_{(t)}$ $-$ social-learning," where "social-learning" is the parameter for the rate of social transmission. Again, the sequence is identical for pro-environmental behavior.

Niche Construction

Third, behaving can lead to niche construction. For example, if an agent behaves pro-environmentally, it can flip one of the patches in its Moore neighborhood (its surrounding eight patches) to a pro-environmental affordance (thus increasing the likelihood of encountering a pro-environmental affordance in the future and effectively making the environment more predictable; see Behavior Shapes the Environment). The procedure is identical for non-environmental behavior. The probability for niche construction is defined by the parameters "construct-pro" (for pro-environmental niche construction) and "construct-non" (for non-environmental niche construction).

Other Processes

Finally, if mutations are turned on, on each tick agents have a chance of mutating their pro-env and non-env values by a slight amount. This is analogous to external influence or the influence of factors not captured by the model. This produces more jagged data more resemblant of real-world observations. We use mutations only in empirical validation. All behaviors in the model are sequential: an agent completes the full set of actions before passing on control to the next agent. The order of agents is read randomly on each tick.

DATA AND CODE AVAILABILITY

All data (.CSV) and code (R) used for analysis are available on GitHub: https://github.com/roopekaaronen/affordance. The agent-based model (NetLogo) with code is available at https://www.comses.net/codebases/c2feceb8-d9c4-4637-8f27-fda49c7dc4f3/releases/1.2.0/.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.oneear.2020.01.003.

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AUTHOR CONTRIBUTIONS

R.O.K. was the main contributing author for the manuscript, model, and analysis. N.S. supervised the project and oversaw the development of the manuscript, model, and analysis.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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One Earth, Volume *2*

Supplemental Information

Cultural Evolution of Sustainable Behaviors: Pro-environmental Tipping Points in an Agent-Based Model

Roope Oskari Kaaronen and Nikita Strelkovskii

Supplemental Experimental Procedures

Software

In this research article and NetLogo (version 6.1.0) model, we use NetLogo's native BehaviorSpace tool for parameter sweeping, and NetLogo's BehaviorSearch for Genetic Algorithms [1]. We use R [2] and R Studio [3] and R packages tidyverse [4], factoextra [5], Hmisc [6], plyr [7], RColorBrewer [8], reshape2 [9], gridExtra [10] and nlrx [11] for data analysis and visualisation.

ODD Protocol

The following model description follows the ODD (Overview, Design concepts, Details) protocol for describing agent-based models [12,13].

1. Purpose

This model illustrates the cultural evolution of pro-environmental behaviour patterns. It shows how collective behaviour patterns evolve from interactions between agents and agents (in a social network) as well as agents and the affordances within a niche. More specifically, the cultural evolution of behaviour patterns is understood in this model as a product of:

1. The landscape of affordances (action opportunities) provided by the material environment,
2. Individual learning and habituation,
3. Social learning and network structure,
4. Personal states (such as habits and attitudes), and
5. Cultural niche construction, or the modulation of affordances within a niche.

More particularly, the model illustrates how changes in the landscape of affordances [14] can trigger nonlinear changes in collective behaviour patterns. The model also shows how several behavioural cultures can emerge from the same environment and even within the same network.

The model is an elaboration of Kurt Lewin's [15] heuristic equation, $B = f(P, E)$, where behaviour (B) is a function (f) of the person (P) and the environment (E). The model introduces several feedback loops (1–5 above) to Lewin's equation, and thus provides a framework for studying the evolution of dynamical and complex behavioural systems over time. The model should be considered an abstract model, since many of its parameters are unspecifiable due to limits to current understanding of human (social) behaviour. However, the model can be tuned to replicate real-world macro patterns, and be used as a sandbox environment to locate tipping points in social systems. In the present manuscript, for example, we use the model to reproduce real-world patterns of bicycle and car use in Copenhagen.

2. Entities, state variables, and scales

The model includes three types of agents: human individuals, represented by mobile circle-shaped agents (or 'turtles' in NetLogo lingo), affordances (static patches that occupy grid cells) and links (which connect agents in a social network).

Individuals: Agents represent a single human being, located within a broader collective social network and ecological niche. Each individual has two personal states. These personal states correspond to the individual's probability of engaging with a specific kind of affordance. Affordances are opportunities for action provided by the environment. The two personal states in this model are *pro-env* and *non-env*. The former, *pro-env*, defines the probability of an individual to engage with pro-environmental affordances, and the latter, *non-env*, defines the probability of an individual to engage with non-environmental affordances.

The personal states of individual agents are sampled from a normal distribution with mean values *initial-pro* (for *pro-env*) and *initial-non* (for *non-env*), and SD 0.15. This standard deviation is roughly in line with empirical data related to environmental attitudes and self-reported behaviours [16]. Owing to the model's probabilistic representation of human behaviour, the values of *pro-env* and *non-env* must be bounded between 0 and 1. More specifically, the model assigns individual boundaries for the *pro-env* and *non-env* of each agent. The bounds are sampled from a normal distribution with mean values 0.2 (lower bound) and 0.8 (upper bound), with SD 0.05.

Individuals are coloured based on their personal states. This is purely cosmetic, but it aids in noticing changes in personal states. If *pro-env* > *non-env*, the agent is coloured black. If *non-env* > *pro-env*, the agent is coloured red.

Links: Individual agents are embedded in a social network which is connected by links. The model supports four types of networks: the Klemm-Eguíluz model (highly clustered scale-free network), the Watts–Strogatz model (small-world network), the Barabási–Albert model (scale-free network with preferential attachment) and the Erdős–Rényi model (random network). All network edges (links) are undirected (bidirectional).

The default network choice is the Klemm-Eguíluz model [17]. The Klemm-Eguíluz algorithm generates a network based on a finite memory of the nodes (agents), creating a highly clustered and scale-free network (see Figures S2–S4). The Klemm-Eguíluz model was chosen since it represents two features we know to characterize social systems: Societies have hubs (the network degree distribution follows a power law distribution, i.e. it has scale-free properties) and societies have highly clustered local communities (social networks have high clustering coefficients) (ibid.). See Klemm and Eguíluz [17] and Caparrini [18] for descriptions of how Klemm-Eguíluz model works, as well as Prettejohn et al. [section 3.4 in 19] for useful pseudocode. We set the default Klemm-Eguíluz model's parameter *m0* (initial number of agents) to 5 and μ (probability to connect with low degree nodes) to 0.9.

Figure S1. Class diagram (UML).

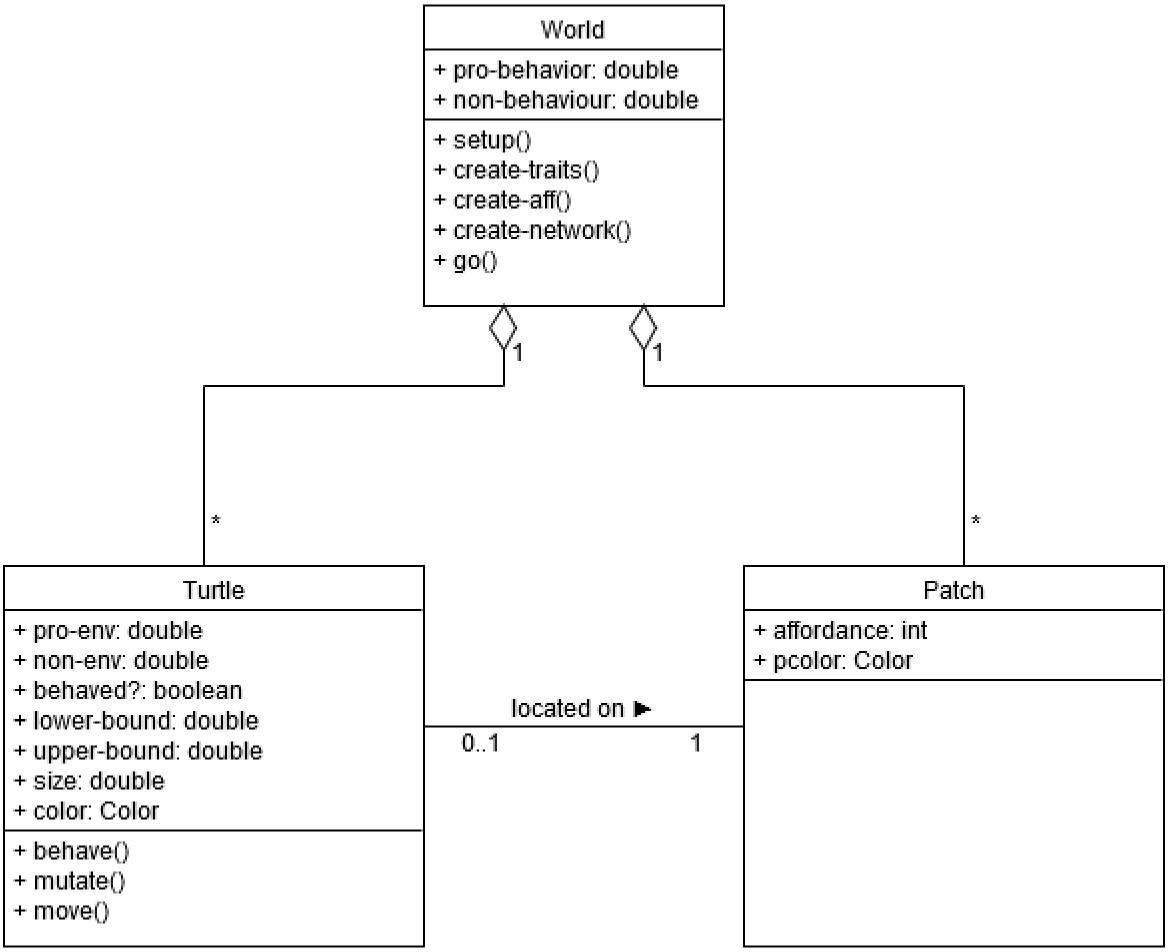


Figure S2. Network degree distribution. A representative plot of the network degree distribution from a single model run with 300 agents. Notice how some agents have amounts of links that greatly exceed the mean (black dashed line) and median (red dashed line).

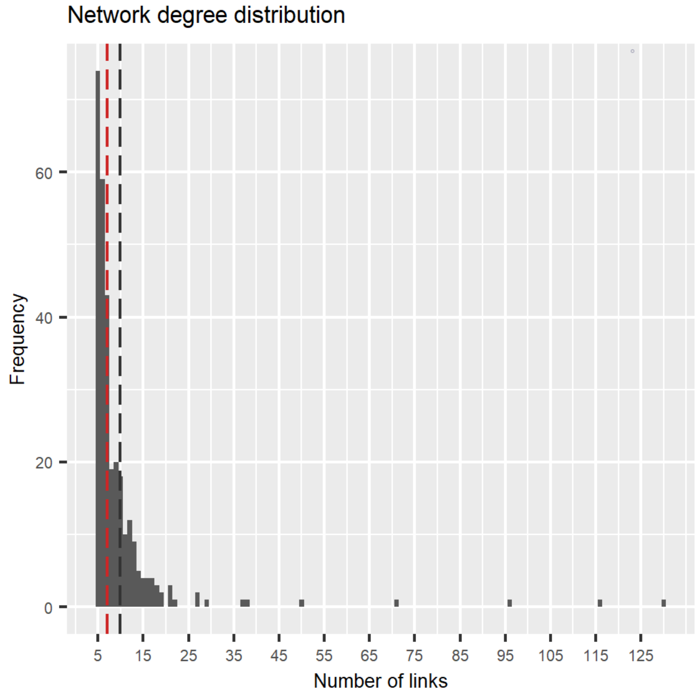


Figure S3. Cumulative network degree distribution. 1000 simulations (total of 300,000 agents) on a logarithmic scale. Notice the scale-free density distribution and relative infrequency of agents with above 150 direct links. Mean links are signified by the black dashed line and median by the red dashed line.

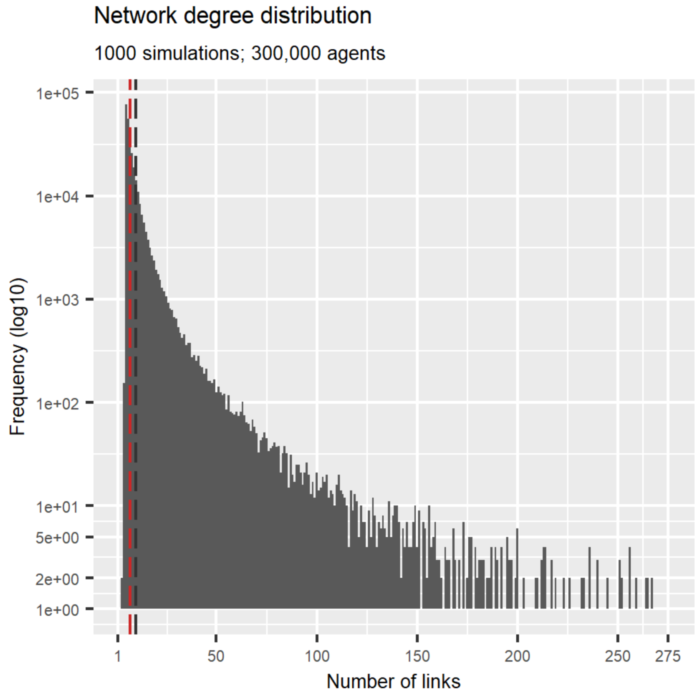
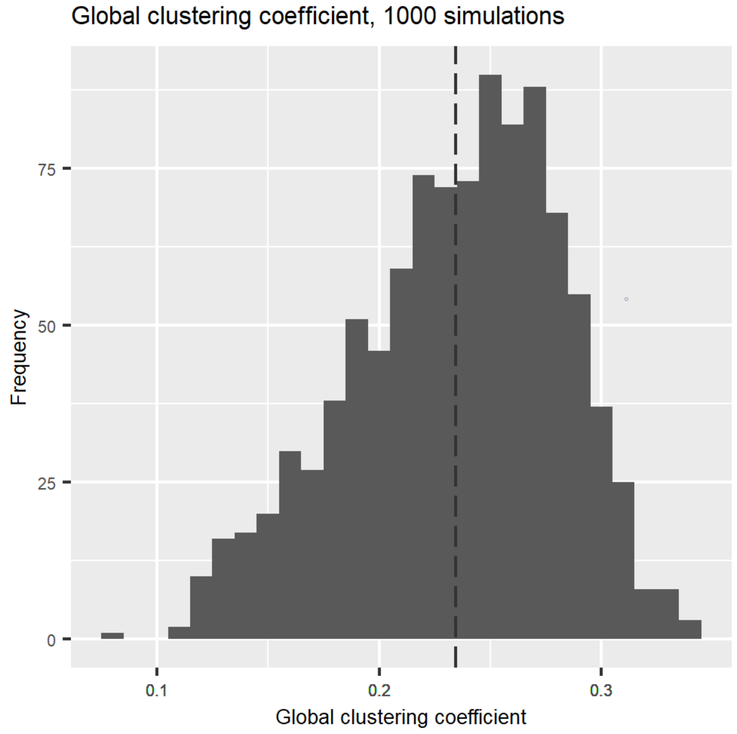


Figure S4. Global clustering coefficients. Histogram with 1000 runs with 100 agents. Global clustering coefficients are calculated based on triplets of nodes. Triplets are three nodes which are connected either by two (open triplet) or three (closed tripled) edges (links). The global cluster coefficient is the number of closed triplets in a network divided by the total number of triplets. Dashed line is at the mean global clustering coefficient, 0.24.



Patches (environment): Patches represent the action-opportunities, or affordances, within the environment. An affordance is the functional relevance of the environment for an individual. The model has two affordances: One represents an opportunity for pro-environmental behaviour (represented by a violet patch) and one represents an opportunity for environmentally harmful behaviour (sky-blue patch). The latter are from here on referred to as non-environmental affordances. The affordances of the environment are therefore binary in this model, even though nothing prevents the addition of more kinds of affordances. Affordance-patches occupy the two-dimensional grid of the model. The grid wraps horizontally and vertically (i.e., it is torus-shaped). The total area of the grid is an arbitrary 201x201 patches.

Scales: The model can be adapted to represent different spatial and temporal scales. One time-step can be understood to either represent one instance of behaviour per agent, or a collection of behaviours. In the abstract version of the model, the spatial and temporal scales are not specifically defined. In empirical validation, the spatial area of the model represents the city centre of Copenhagen, with each tick representing one day.

3. Process overview and scheduling

The submodels of the model are described in more detail and pseudocode in the *Submodels* section. In this section, we describe a brief process overview.

Setup: The model begins with a setup phase where the patches, agents and links are created. Ticks are reset after the setup, so all setup processes occur before the first timestep.

First, the social network (agents and links) is created. This will create a network with individuals specified by the parameter *number-of-agents*.

Second, each agent is assigned two personal states, *pro-env* and *non-env*.

Third, affordances are created. Affordances are binary patches-own variables: value 0 signifies a non-environmental affordance, and value 1 a pro-environmental affordance. First, all patches are assigned with a non-environmental affordance (and coloured sky-blue). Subsequently, the proportion of patches designated by the parameter *pro-amount* are turned into pro-environmental affordances. Therefore, the parameter *pro-amount* corresponds to the initial proportion of pro-environmental affordances within the total landscape of affordances.

Go: The 'Go' procedure is the heart of the model.

First, agents behave. If the agent is on a pro-environmental affordance, it will interact with it with the probability of P(*pro-env*). For example, if an agent's personal state *pro-env* is 0.5, it has a 50% chance of interacting with a pro-environmental affordance.

Likewise, if the agent is on a non-environmental affordance, it will interact with it with the probability of P(*non-env*). Again, if an agent's personal state non-env is 0.7, it has a 70% chance of interacting with a non-environmental affordance.

A while-loop ensures that each agent behaves once every turn. Each agent owns a binary value, *behaved?*, which signifies whether it has behaved, or actualized an affordance, during the current tick. If *behaved?* is TRUE, the agent will stop attempting to behave after completing the behaviour commands (including steps 1–5 below).

Once an agent behaves successfully, a sequence of procedures launched in the following order.

1. If the agent behaved pro-environmentally (i.e., it actualizes a pro-environmental affordance), it will increase its current personal state *pro-env* by the amount of *asocial-learning* and decrease its current *non-env* by the amount of *asocial-learning*.

   Conversely, if the agent behaved non-environmentally (i.e., it actualizes a non-environmental affordance), it will increase its current *non-env* by the amount of *asocial-learning* and decrease its current *pro-env* by the amount of *asocial-learning*.

2. If *niche-construction* is TRUE (niche construction is turned on) and if the agent behaved pro-environmentally, with probability *construct-pro* it will ask one of the eight patches in its Moore neighbourhood to turn into a pro-environmental affordance (which is then coloured in violet). *construct-pro* therefore defines the rate of pro-environmental

niche construction. The procedure is identical for non-environmental niche construction (following non-environmental behaviour), whose rate is defined by *construct-non.* Rates of niche construction are controlled for number-of-agents. This way, adding more agents to the simulations does not add to the rate of overall niche construction. This is necessary because the area (grid) of the model is held constant.

3. If *networks* is TRUE and if the agent behaved pro-environmentally, it will engage in social learning with its network neighbours (the agents to which it is directly connected to by a link). Following pro-environmental behaviour, the agent will ask its network neighbours to increase their current *pro-env* by the amount specified by parameter *social-learning*, as well as to decrease their current *non-env* by the amount specified by parameter *social-learning*. Again, the procedure is similar after non-environmental behaviour, except this results in an increase of *non-env* and decrease of *pro-env* by the amount of *social-learning*.

4. The agent will bound its personal states *pro-env* and *non-env*. If the agent's personal state is above its upper bound or below its lower bound, it will set its personal state to its upper and lower bound, respectively.

5. If mutate? Is TRUE, at each tick, the pro-env and non-env of all agents have a chance of mutating. The default probability for mutation (*mutate-prob*) is 0.005, and the default rate for mutation (*mutate-rate*) is 0.05. The probabilities for increasing or decreasing pro-env and non-env values (of all agents) are equal, i.e. mutation is not biased to any direction.

After each behaviour or attempt to behave, agents move in a random forward direction between 45 degrees right and 45 degrees left from their current heading. In one tick (timestep) agents will continue moving until they have behaved, i.e. until they have successfully interacted with an affordance.

The aforementioned steps are sequential: An agent completes the full set of actions before passing on control to the next agent. The order of agents is read in a random order on each tick.

4. Design concepts

Basic principles.

The model design elaborates on social psychologist Kurt Lewin's [15] heuristic equation: $B = f(P, E)$. Here, behaviour (B) is a function (f) of the person (P) and its environment (E).

The model adds five dimensions of detail into Lewin's equation.

1. The environment affords a variety of opportunities for action, or affordances ($E \rightarrow B$).
2. Behaviour modulates personal states through processes of habituation and individual learning ($B \rightarrow P$).
3. Personal states, such as habits and intentions, drive behaviour ($P \rightarrow B$).
4. Behaviour shapes the environment through processes of niche construction ($B \rightarrow E$).
5. Feedback loops 1–4 all occur within a social network where behaviour is transmitted via social learning ($B_{myself} \rightarrow P_{neighbors}$ and $B_{neighbors} \rightarrow P_{myself}$).

These assumptions are elaborated in detail in the manuscript's section Model Assumptions.

The basic principles can be summarized as follows: Through processes of individual and social learning as well as niche construction, any behaviour at time t will have an effect on the behaviour of an agent and other agents at time $t+1$. The model therefore presents a dynamical systems approach to the emergence of human behaviour, where the unit of study is a tightly coupled human-environment system – a dynamical system which evolves over time and can behave in nonlinear ways due to positive feedback-loops.

Emergence.

The model produces a complex and dynamical system which exhibits several kinds of emergent behaviour.

Firstly, the model displays nonlinearities in the development of behavioural cultures (collective behaviour habits). The behaviour of the agents in the network can be steady for long periods of time, only to be followed by abrupt phase transitions into new states (this is illustrated in more detail in the Results section of the manuscript).

Second, the model illustrates how two different behavioural cultures can emerge from the same environment, and even in the same social network. This is a macro-level pattern that is known (from studies of cultural evolution) to occur in real-world societies [20].

Third, the model has several leverage points. For instance, a small change (e.g., 5–10%) in the initial composition of affordances in the landscape can have radical effects on the evolution of the behavioural cultures. Thus, in a way which is typical to complex emergent systems, the model is sensitive to initial conditions, which makes its evolution difficult to predict at certain parameter ranges.

Fourth, whilst the model always starts with a random composition of the affordance landscape, this landscape gets more structured over time as individuals construct the niche around them.

Adaptation.

Through processes of individual and social learning, agents adapt their personal states to their behaviour and to their immediate social environment. Moreover, agents construct their environment to be more predictable by constructing niches which are in line with past behaviour.

Objectives.

Agents engage in active attempts to behave successfully (actualize an affordance) and to create an environment where past behaviour patterns are increasingly more likely.

Learning.

The model includes two learning processes, individual and social learning. Individual (asocial) learning occurs after behaviour and affects only the agent who behaved. Individual learning is thus a product of individual behaviour. Social learning occurs in the social network an agent is embedded in.

The rates of individual and social learning depend on the chosen representation of behaviours and time-units. Realistic rates of individual and social learning are therefore difficult to specify. However, by studying real-world patterns, it might be possible to infer reasonably accurate rates of social and individual learning (see section Empirical Validation of the manuscript).

Prediction.

Agents do not estimate future conditions or consequences of their decisions.

Sensing.

Agents sense the (colour of the) patch they are currently on as well as their network neighbours and neighbours' behaviour. Agents also sense their physical vicinity, i.e. the patches in their Moore neighbourhood (the 8 patches surrounding the patch they are currently on).

Interaction.

After behaving, agents interact with their network neighbours. This involves both influencing the network neighbours as well as being influenced by each network neighbour (both defined by the rate of *social-learning*). Niche construction also influences the behaviour of other agents, and is thus an indirect form of social interaction.

Stochasticity.

The following processes rely on random sampling:

The initial personal states of agents are sampled from a normal distribution (see section 2 of ODD protocol above). The initial configuration of affordances on the grid is random (the proportion of pro-environmental affordances, however, is fixed by the parameter *pro-amount*). The movement of agents on the grid is a random walk through the landscape of affordances. Each instance of behaviour and niche construction makes use of a floating random number generator. The model supports the use of a fixed random seed for replicability (if *random-seed?* is TRUE, a random seed can be fixed with the *rseed* parameter).

Collectives.

Individuals belong to a social network and construct their niche, as defined above. Individuals take part in shaping the collective network and niche which, in turn, shapes their behaviour.

Observation.

Observation generally involves tracking mean or specific values over time. The most relevant variables are the global variables *pro-behavior* and *non-behavior*, which track the total amount of pro-environmental and non-environmental behaviour during each tick.

Parameter sweeps are conducted via NetLogo's native BehaviorSpace tool.

5. Initialization

The initialization of the model is allowed to vary among simulations. Since many values, such as the personal states of agents, are randomly sampled, each model run will differ from the next even when run with the same parameter values.

However, the model supports the use of a fixed random seed for replicability (if *random-seed?* is TRUE, a random seed can be fixed with the rseed parameter).

The initial state of the model at $t = 0$ will depend on the parameters *initial-pro, initial-non, pro-amount* and the network parameters (*networks*, *network-type*) as defined above.

In the abstract version of the model, the initial states are arbitrary. The abstract model can be used to study the dynamics and sensitivities of the model's general structure.

In empirical validation, the initial states of the model are tuned to reproduce real-world patterns, or the cycling and driving habits of people in central Copenhagen.

6. Input data

The model does not use input from external sources such as data files or other models.

7. Submodels

In the following, the processes mentioned in *Process overview and scheduling* (above) are described in more detail in pseudocode, flowcharts (UML diagrams) and natural language. Pseudocode is written by editing NetLogo code to resemble natural language. Whilst the descriptions below are comprehensive, please also refer to the fully annotated model code for details. The following section documents the *SETUP* submodels (*Social network*, *Personal states and Affordances*) and the *GO* submodels (*Behavior* and *Mutate*). *Behavior* includes descriptions of the processes of individual learning, niche construction and social learning.

SETUP

Social network

Since fully a full description of the Klemm-Eguíluz model would require a chapter-length analysis, we refer the reader to Caparrini's Complex Networks Toolbox [18] for a description of the Klemm-Eguíluz small-world-scale-free network (we adapted, with permission, Caparrini's code for the present model). A full pseudocode description of the Klemm-Eguíluz model is openly accessible in Prettejohn, Berryman and McDonnell's [19] chapter '3.4 Klemm and Eguílez

Small-World-Scale-Free Network'. A full mathematical description of the model is also available in Klemm-Eguíluz' original work [17].

Personal states

Personal states are created in the model setup. In pseudocode,

```
to set personal states
for each turtle in the list of all turtles [
  Set pro-env: sample a random value from a normal distribution with
  mean of initial-pro and a standard deviation of 0.15.
  Set non-env: sample a random value from a normal distribution with
  mean of initial-non and a standard deviation of 0.15.
  Set lower-bound: Set a lower bound for non-env and pro-env from a
  random normal distribution with mean 0.2 and SD 0.05.
  Set upper-bound: Set an upper bound for non-env and pro-env from a
  random normal distribution with mean 0.8 and SD 0.05
  ]
  end
```

Affordances

Affordances are patches-own variables. Affordances are created with the following procedure (pseudocode):

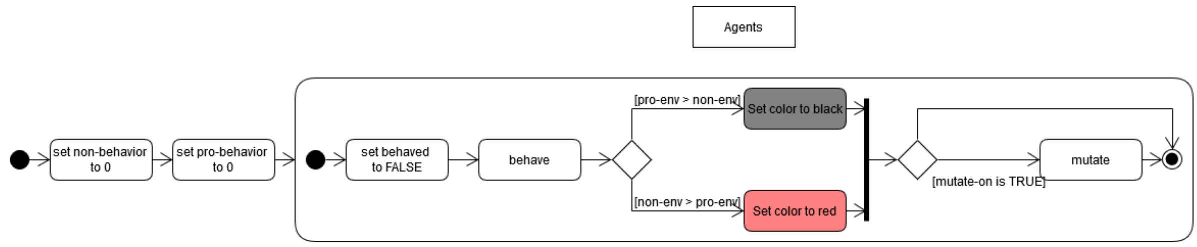
```
to create affordances
let total-patches be total count of patches
  ask all patches [
     set affordance to 0 ;; non-evironmental affordance
```

```
      set color to sky-blue ]
  ask n-of (total-patches * pro-amount) patches [
      set affordance to 1 ;; pro-environmental affordance
      set color to violet]
end
```

GO

The go-procedure begins with each agent resetting their global *pro-behavior* and *non-behavior* variables to 0 (these global variables measure the total pro- and non-environmental behaviours of all agents at the end of each tick). Then, agents set their *behaved?* variable (turtles-own variable) to FALSE. The *behaved?* variable ensures that each agent behaves (either pro- or non-environmentally) only once during a tick. After this, agents behave.

Figure S5. Go procedure, activity diagram (UML).



Behavior

This submodel is the heart of the model. It defines how agents interact with the environment and other agents. Since the procedure is identical for both pro-environmental and non-environmental behaviours, only pro-environmental behaviour is described here. To implement non-environmental behaviour, simply duplicate the code and replace ‘pro-environmental’ (value 1) patch with ‘non-environmental’ (value 0), ‘violet’ with ‘sky-blue’, and *pro-env* with *non-env* (and vice versa, *non-env* with *pro-env*). The processes of habituation, niche construction and social learning are included in this submodel, and are described below in pseudocode.

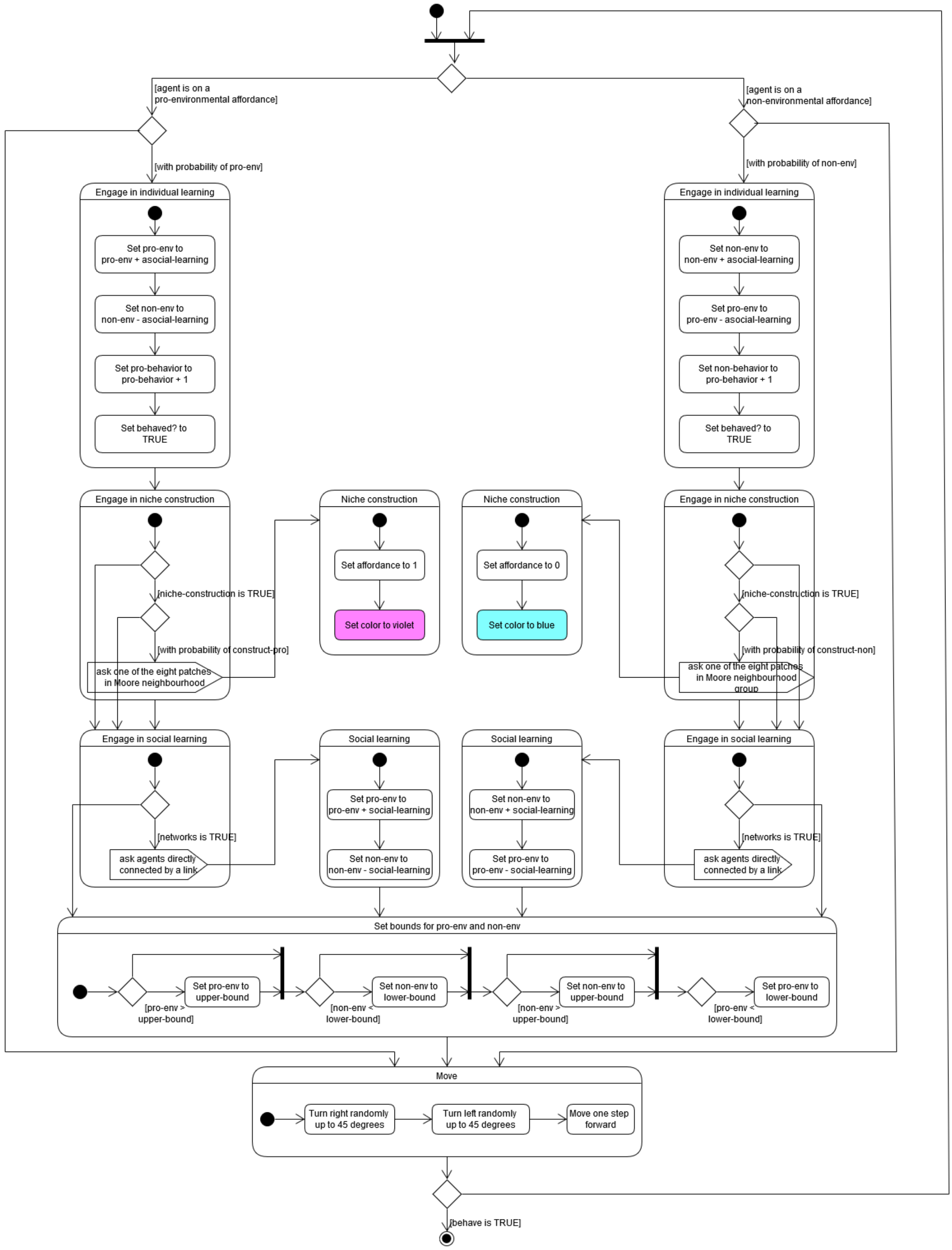
```
to behave
 while behaved? is FALSE [ ;; Start of while-loop
      if the patch the agent is currently on is pro-environmental
      and random-floating number in range [0,1] is smaller than
      pro-env [
;; Engage in individual learning
      set pro-env to (pro-env + asocial-learning)
      set non-env to (non-env - asocial-learning)
      set pro-behavior to (pro-behavior + 1)
      set behaved? to TRUE
;; And still complete the following commands (we are still in the
while-loop)

;; Engage in niche construction
if niche-construction is TRUE [
      if random-floating number in range [0,1] is smaller than
      (construct-pro / number-of-agents) [
         ask one-of patches in Moore neighborhood [
            set affordance to 1
            set color to violet ]
               ]
            ]
```

```
;; Engage in social learning
if networks is TRUE [
      ask link-neighbors [
        set pro-env to (pro-env + social-learning)
        set non-env to (non-env - social-learning)
            ]
      ]
]

;; Set bounds for pro-env and non-env
if pro-env > upper-bound [set pro-env to upper-bound]
if non-env < lower-bound [set non-env to lower-bound]
if non-env > upper-bound  [set non-env to upper-bound]
if pro-env < lower-bound [set pro-env to lower-bound]

;; Finally, move.
turn right randomly up to 45 degrees
turn left randomly up to 45 degrees
move one step forward
] ;; End of while-loop, and end the behave procedure
end
```

Mutate

```
to mutate

if mutate-on? = TRUE [

let mutate-probability 0.005

let mutate-rate 0.05

if random-floating number in range [0,1] is smaller than mutate-
probability [

    ask turtles [ set pro-env to (pro-env + mutate-rate)]]

if random-floating number in range [0,1] is smaller than mutate-
probability [

    ask turtles [ set non-env to (non-env - mutate-rate) ]]

;; ...and so on for all four possible configurations (mutation is
not biased to any direction.)

if random-floating number in range [0,1] is smaller than mutate-
probability [

    ask turtles [ set non-env to (non-env + mutate-rate) ]]

  if random-floating number in range [0,1] is smaller than mutate-
probability [

    ask turtles [ set pro-env to (pro-env - mutate-rate) ]]

]

end
```

Figure S6. The 'behave' submodel, activity diagram (UML).



Sensitivity Analysis

Local Sensitivity Analysis: OFAT Testing

We begin by testing our model's sensitivities based on one-factor-at-a-time (OFAT) sensitivity analysis. OFAT sensitivity analysis 'consists of selecting a base parameter setting (nominal set) and varying one parameter at a time while keeping all other parameters fixed' [21]. It is therefore referred to as a local sensitivity analysis method. For local sensitivity testing, we use the parameter values as defined by Table S3 (the abstract model run), since its output is arguably more intuitive to understand (than the parameter values used for empirical validation), and it is much less computationally demanding. For data visualisation, we use raincloud plots [22], which illustrate the distribution of data points (in this case, the proportion of pro-environmental behaviour at the final timestep, 2000) and a boxplot with medians and ± 1 standard deviations. Since the mechanism for initial-pro and initial-non, as well as construct-pro and construct-non, are identical, only the pro-environmental variants of these parameters are analysed. This produces a total of 7 plots, shown below.

Figure S7. Sensitivity test 1. The model is especially sensitive to the initial proportion of pro-environmental affordances. This is, however, expected on the basis of results such as Figures 2A and 2B. At extreme values such as when pro-amount is larger than 0.75, most agents will behave pro-environmentally.

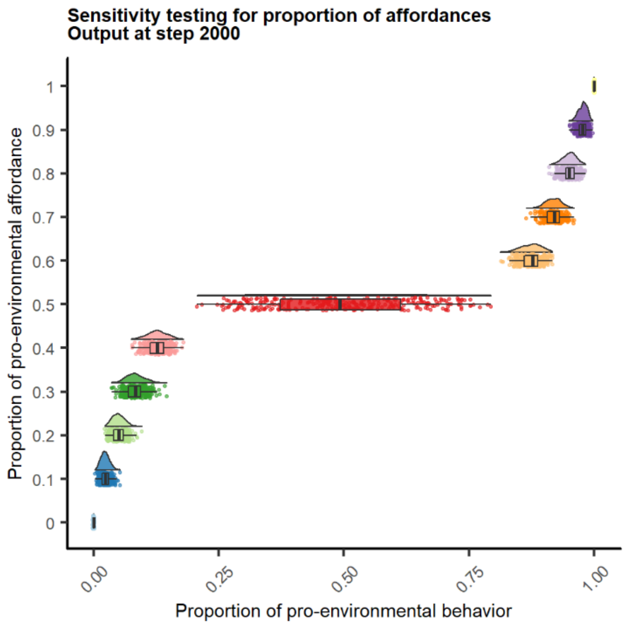


Figure S8. Sensitivity test 2. The model is particularly robust against changes in the rate of individual (asocial) learning.

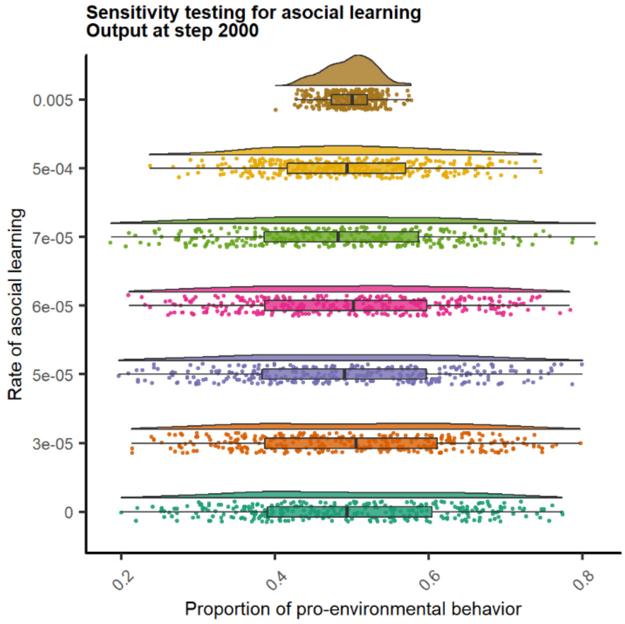


Figure S9. Sensitivity test 3. Higher rates of pro-environmental niche construction will lead to more extreme results in the adoption of pro-environmental behaviour. This effect was also seen and explained in the Results section of the present manuscript.

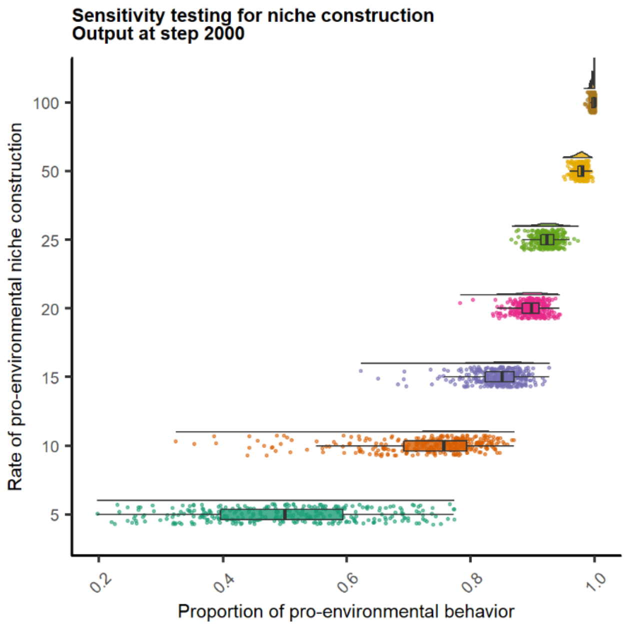


Figure S10. Sensitivity test 4. The network density (minimum degree of connection, or *m0* in the Klemm-Eguíluz model) has a notable effect on outcomes in pro-environmental behaviours. The reasoning is intuitive: When networks are denser, more social learning and transmission occurs, which leads to more polarized end results as the society of agents converges into a uniform behavioural unit or culture (notice how the density distribution of degree connection 20 approaches what seems like a bimodal distribution).

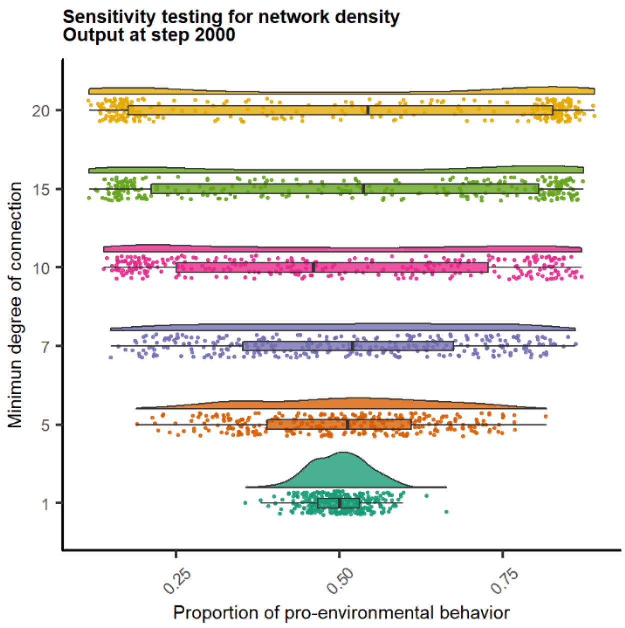


Figure S11. Sensitivity test 5. Importantly, the model is robust against the total number of agents. Due to computational constraints, we do not run the model with over 1000 agents. When the model has over 100 agents, the results are similar. The default value for number-of-agents, 300, can thus be justified.

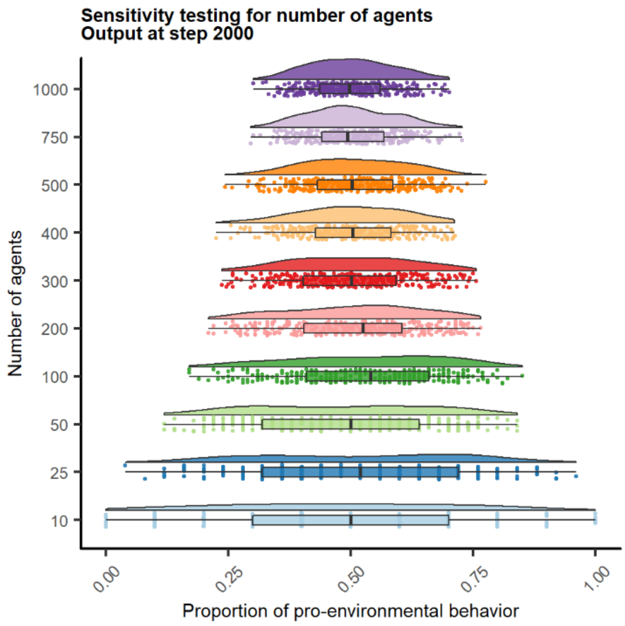


Figure S12. Sensitivity test 6. The effect of initial pro-environmental personal states on the outcome of the model is considerable, and similar in logic to the initial composition of affordances (Figure S7). Notice, however, that in global sensitivity testing, this effect is shown to be less robust when other parameters are allowed to vary.

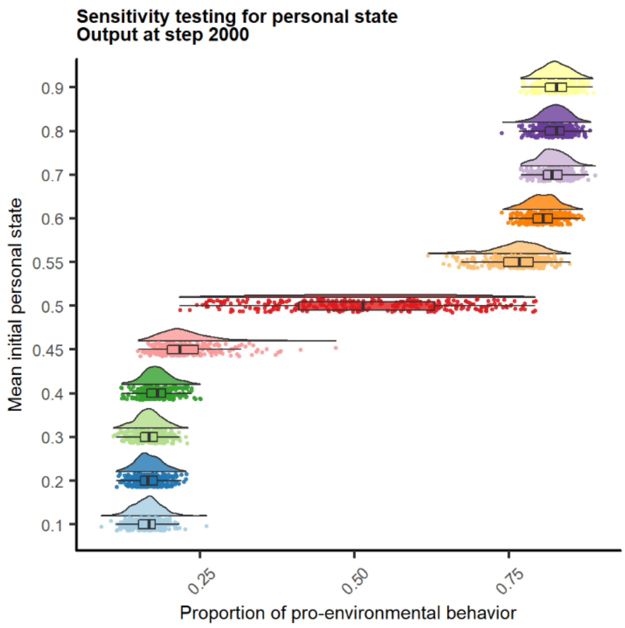
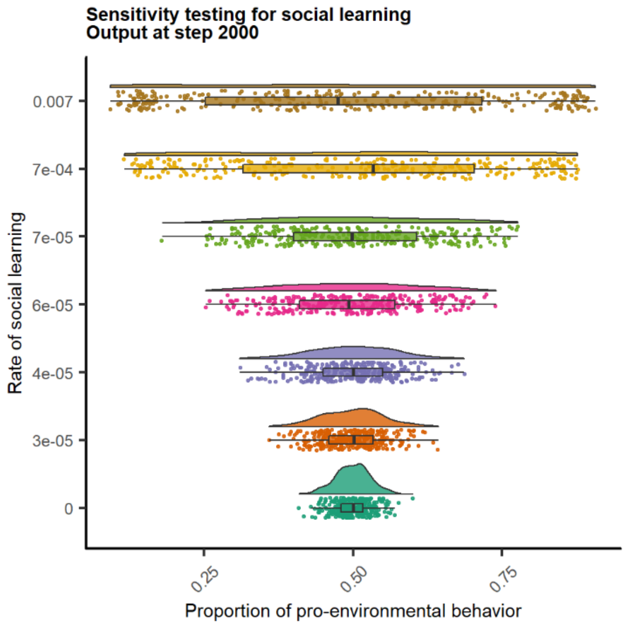


Figure S13. Sensitivity test 7. Similarly to Figure S10 (network density), the rate of social learning has a considerable effect on model outcomes, particularly at extreme values (i.e., ten- or twentyfold to the rate used in the Results section). The model is quite robust against more moderate changes in the rate of social learning. Again, the reasoning is intuitive: The more the rate of social learning is increased, the more social transmission occurs, which leads to more polarized end results as the society of agents converges into a uniform behavioural unit or culture.



Global sensitivity analysis: Latin hypercube sampling

We use Latin hypercube sampling (LHS) as our method for global sensitivity analysis. LHS ensures that each of the model's input variables have all portions of their distribution represented by input values [23]. LHS is simply a K-dimensional extension of Latin square sampling (ibid.), and is commonly used for global sensitivity testing [24]. See e.g. [24] or [23] for more details on LHS. We use the R package nlrx [11] to generate our Latin hypercube samples. We sample our input values from the ranges specified in Table S1. The values were selected on the basis of the OFAT sensitivity tests. We excluded extreme parameter values (which would lead to very predictable and extreme model results, such as when pro-amount is close to 1), but still allow the model to run on a wide range of input values.

Table S1. Parameter ranges for global sensitivity analysis.

Model parameter	**Range**
number-of-agents	[100, 1000]
social-learning	[0.0002, 0.0008]
asocial-learning	[0.0002, 0.0008]
pro-amount	[0.33, 0.66]
initial-pro	[0.33, 0.66]
initial-non	[0.33, 0.66]
construct-non	[0, 10]
construct-pro	[0, 10]
network-param	[3, 7]
mu	0.9

Figure S14. Sensitivity test 8. 300 parameter sets are sampled from the ranges specified in Table S1. The model is run 5 times on each parameter sample, with a different random seed. The lines in this plot illustrate the range of the outcomes of each parameter sample, from min value to max value. Overall, the model has a clear tendency of converging to a state of either high or low pro-environmental behaviour. This is unsurprising, given the results seen in Figures 2–4. This effect will be less drastic if the model is run for less than 2000 ticks or if the range of parameters such as pro-amount is decreased.

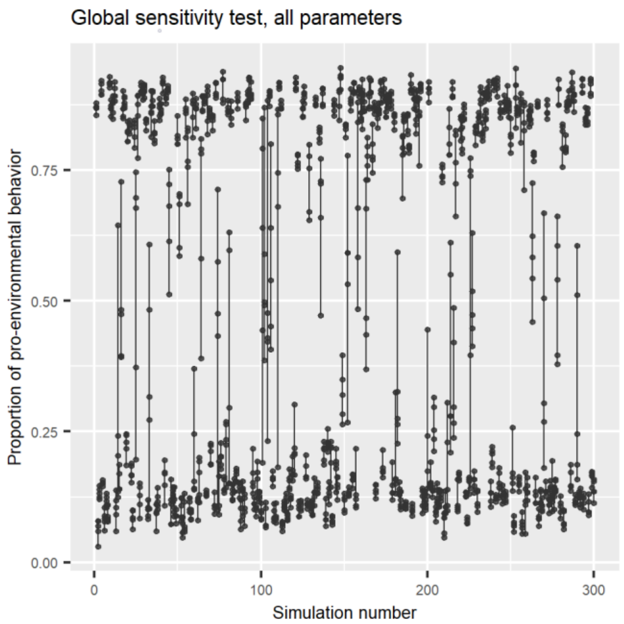


Figure S15. Sensitivity test 9. Even when all other parameters are allowed to vary freely, the nonlinear effect of pro-environmental affordances on pro-environmental behaviour remains. This figure therefore illustrates that the phase transition effect seen in Figures 2A and 2B is very robust.

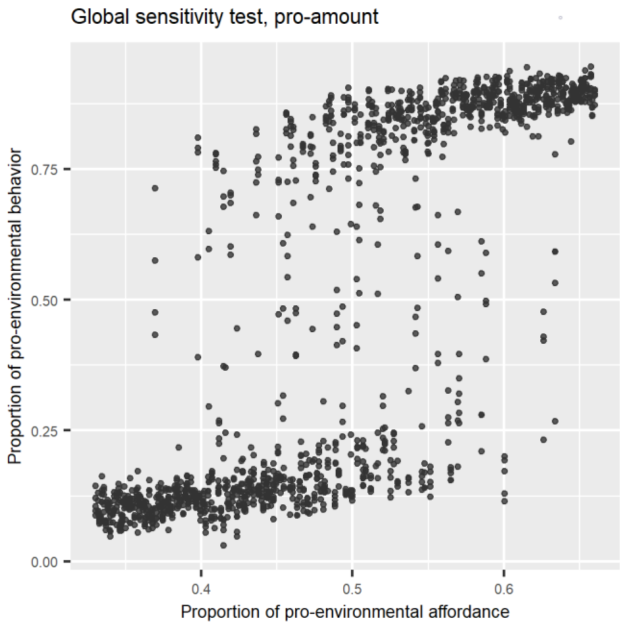
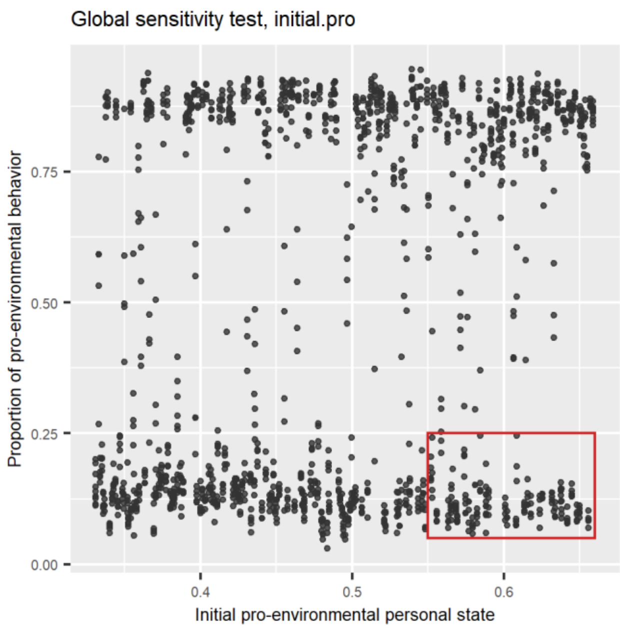


Figure S16. Sensitivity test 10. When other parameters are allowed to vary, initial-pro (the mean initial pro-environmental personal state) has a less apparent effect on behaviours than seen in Figure S12 (where an OFAT test was run on initial-pro). Notice how initial pro-environmental personal states often do not translate into sustained pro-environmental behaviour (highlighted by the red box). This is most likely because of either a lack of pro-environmental affordances, or the interference of a high initial-non value (i.e., counteracting personal states).



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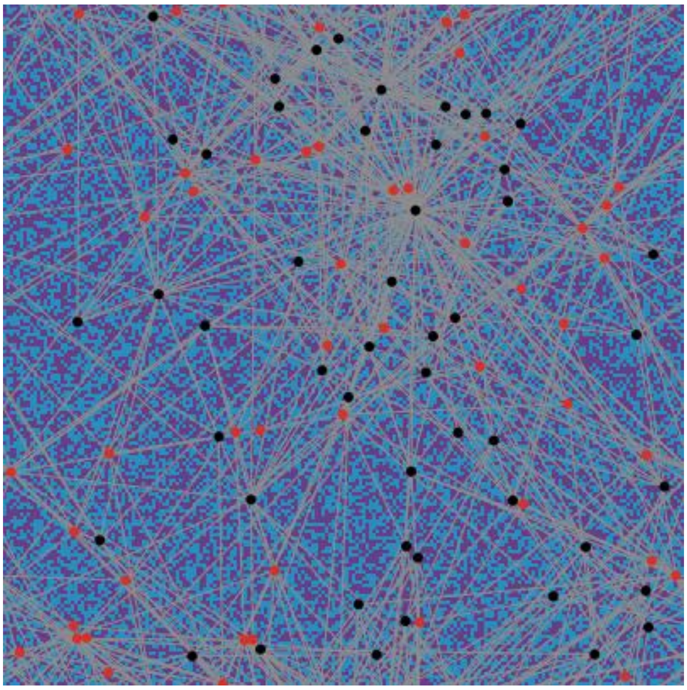
Supplemental Figures

Figure S17. A screenshot of the spatially explicit NetLogo model. Here, 100 agents (circle-shapes) are connected to each other in a Klemm-Eguíluz network. Agents coloured in black are more pro-environmentally than non-environmentally disposed, and vice versa for agents coloured in red. The network is represented with grey links connecting the agents. Notice how some agents are much more connected than others. The environment consists of two kinds of patches, pro-environmental affordances (violet) and non-environmental affordances (sky-blue). Agents move around the grid in a random walk. The torus-shaped world wraps around horizontally and vertically.



Supplemental Tables

Table S2. Parameters. The model's parameters, descriptions of parameters, and ranges of possible parameter values.

Model parameter	**Description**	**Possible range**
number-of-agents	Total number of agents.	[1, 1000]
social-learning	Rate of social transmission of behaviour.	[0, 1]
asocial-learning	Rate of individual learning and habituation.	[0, 1]
pro-amount	Initial proportion of pro-environmental affordances in the landscape of affordances.	[0, 1]
initial-pro	Defines the initial pro-environmental personal state, pro-env, which is the probability of interacting with pro-environmental affordances when encountered.	[0, 1]
initial-non	Defines the initial non-environmental personal state, non-env, which is the probability of interacting with non-environmental affordances when encountered.	[0, 1]
construct-non	Probability of constructing a non-environmental affordance.	[0, number-of-agents]
construct-pro	Probability of constructing a pro-environmental affordance.	[0, number-of-agents]
network-param	*m0* in the Klemm-Eguíluz model [17]. Defines the initial complete graph in the network generating algorithm.	[1, number-of-agents]
mu	μ in the Klemm-Eguíluz model [17]. Probability of connecting with low degree nodes. Alters the clustering coefficient of the network. [18]	[0, 1]

Table S3. Parameter values for the abstract model run.

Model parameter	**Value**
number-of-agents	300
social-learning	0.00007
asocial-learning	0.00005
pro-amount	[0, 1]
initial-pro	0.5
initial-non	0.5
construct-non	0 or 10
construct-pro	0 or 10
network-param	5
mu	0.9

Table S4. Parameter values for the Copenhagen simulation.

Model parameter	**Value**
number-of-agents	300
social-learning	0.00007
asocial-learning	0.00005
pro-amount	0.4
initial-pro	0.2
initial-non	0.8
construct-non	0
construct-pro	5
network-param	5
mu	0.9