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

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

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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

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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.5,12 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, 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. 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 “path of least resistance and the default form of life.” Although predicting where or when pro-environmental tipping points emerge remains a difficult, if not impossible, 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” 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 (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. Our conceptual model also includes other characteristics particularly suitable for ABMs, such as heterogeneous populations and emergent collective behaviors arising from simple interactions. Agent-based modeling has become a standard method for studying complex, dynamical, and adaptive systems, 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, for modeling.

ABMs have previously been employed in studying the adoption of various sustainable behaviors and attitudes, including models of norm transmission and evolution, recycling, traffic and transport, farming, energy and risk management, and psychology. 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 emerging 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. 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.” We expand Kurt Lewin’s equation (Equation 1), 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.

Lewin’s equation: \( B = f(P, E) \) (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
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\textsuperscript{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.”\textsuperscript{15}

**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 illustrates the end results of the model at timestep 2,000. Here, the initial proportion of pro-environmental affordances is varied from 0 to 0.5 with intervals of 0.01 and 30 simulation runs for each pro-amout 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 demonstrates the 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\textsuperscript{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
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 reminiscent 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...
affordances is close to linear (see Figure 6A for real-world data composition of affordances over time, even if the development of might not have taken off nearly at the rate that it did. That is, the accelerating rate of cyclists witnessed in the real-world data had invested less into the development of cycling infrastructure, construction. It could be interpreted as suggesting that if the city Copenhagen simulation: the rate of 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.
over, and leveraging environmentally significant behaviors by means of communication or information campaigning has proved to be notoriously difficult.\textsuperscript{2,51,52} Perhaps a more reasonable information-oriented approach to collective behavioral change would be through the redesign of “general ecological information”\textsuperscript{54} 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\textsuperscript{53} and Jane Jacobs\textsuperscript{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”\textsuperscript{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\textsuperscript{21}) and a higher variety of affordances and behaviors.

However, as we have stated above and as has been discussed by many others,\textsuperscript{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.\textsuperscript{56,57} As is generally the case with complex systems, small changes in initial conditions can cause large variance in emergent end results.\textsuperscript{57,58}

Moreover, social and psychological theories might altogether lack formal descriptions of mechanisms essential for modeling.\textsuperscript{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.\textsuperscript{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,\textsuperscript{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\textsuperscript{60} (or indeed both, e.g., with PPGIS\textsuperscript{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.
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This model design is influenced by dynamical systems approaches to cognition and behavior.3,5,31 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 Chemero1 and Lewin,1,2 the model assumes that focusing on only one of either personal states or the environment in insufficient for describing the emergence of behavior:

**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.3,2

The design of the model presented in the present paper expands on Kurt Lewin’s equation (Equation 1).3,2 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 (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).

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**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.1,3 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 the environment because single dynamical systems can have parameters on either 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 psychology1,3,35 and (radical) embodied cognitive science.1 Moreover, dynamical systems approaches to studying or modeling systemic change32 and coupled human-nature systems60 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.32 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.1,3 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.7

**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]).

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Dynamical systems theory is especially appropriate for explaining cognition as interaction with the environment because single dynamical systems can have parameters on either 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 psychology1,3,35 and (radical) embodied cognitive science.1 Moreover, dynamical systems approaches to studying or modeling systemic change32 and coupled human-nature systems60 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.32 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.1,3 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.7
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. 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. 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.

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. 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. 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. 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, Kytta 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
learned sensorimotor skills, (tacit and explicit) knowledge, capabilities, and
Therefore, the personal state as referred to in this paper is much more than
is defined as the totality of an organism’s properties that dispose it to behaving
behavior responds to the probability of interacting with a certain type of affordance.
mental knowledge and environmental awareness does not necessarily translate into pro-environmental behavioral patterns. This discrepancy might be a result of old habits or, simply, the lack of given and easily accessible action opportunities or affordances.

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, 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. Although the roots of niche construction theory lie in evolutionary ecology,^9^ niche construction theory has more recently gained interest in cognitive science^9,10^ and cultural evolution. For present purposes, it suffices to understand niche construction as the construction of non-random biases on behavioral selection pressures.

Through the process of niche construction, we design our environment to afford a large variety of behaviors that reinforce our daily habits and routines. 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.^8,10^ As Wallraff et al. argue,^11^ niche construction “can be viewed as the process whereby agents make their niche conform to their expectations” (see also Constant et al.^12^). 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^13^).

planned behavior^14^ 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.^47,48^ For instance, possession of environmental knowledge and environmental awareness does not necessarily translate into pro-environmental behavioral patterns.^52^ This discrepancy might be a result of old habits or, simply, the lack of given and easily accessible action opportunities or affordances. 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, and so on.

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one-factor-at-a-time (OFAT) sensitivity tests, 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. 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,” 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-amort.”

**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. 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). Although our ABM also supports the Erdős-Rényi model (random network), the Barabási-Albert model (scale-free network with low clustering), and the Watts-Strogatz small-world model (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 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 for a concise definition of these parameters and Klemm and Eguíluz 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, 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 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 0.45.

**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 tick.

**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-envt + asocial-learning” and its non-env to “non-envt − 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-envt + social-learning” and its pro-env to “pro-envt − 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 reminiscent 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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