1-2024

# From Mind to Matter: Patterns of Innovation in the Archaeological Record and the Ecology of Social Learning

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*American Antiquity* (2024), **89**, 19–36
doi:10.1017/aaq.2023.71

ARTICLE

# From Mind to Matter: Patterns of Innovation in the Archaeological Record and the Ecology of Social Learning

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(Received 8 December 2022; revised 19 June 2023; accepted 13 August 2023)

**Abstract**
Archaeology and cultural evolution theory both predict that environmental variation and population size drive the likelihood of inventions (via individual learning) and their conversion to population-wide innovations (via social uptake). We use the case study of the adoption of the bow and arrow in the Great Basin to infer how patterns of cultural variation, invention, and innovation affect investment in new technologies over time and the conditions under which we could predict cultural innovation to occur. Using an agent-based simulation to investigate the conditions that manifest in the innovation of technology, we find the following: (1) increasing ecological variation results in a greater reliance on individual learning, even when this decreases average fitness due to the costs of learning; (2) decreasing population size increases variability in the types of learning strategies that individuals use; among smaller populations drift-like processes may contribute to randomization in interpopulation cultural diffusion; (3) increasing the mutation rate affects the variability in learning patterns at different rates of environmental variation; and (4) increasing selection pressure increases the reliance on social learning. We provide an open-source R script for the model and encourage others to use it to test additional hypotheses.

**Resume**
Tanto la arqueología como la teoría de la evolución cultural pronostican que la variación ambiental y el tamaño de la población impulsan la probabilidad de invención (a través del aprendizaje individual) y su conversión en innovaciones para toda la población (a través de la aceptación social). Utilizamos el estudio de caso de la adopción del arco y la flecha en la Gran Cuenca para inferir cómo los patrones de variación, invención e innovación culturales afectan la inversión en nuevas tecnologías a lo largo del tiempo y las condiciones bajo las cuales podríamos pronosticar que ocurrirá innovación cultural. Exploramos este estudio de caso con una simulación basada en agentes para investigar las condiciones que se manifiestan en la innovación tecnológica. Encontramos que (1) Un incremento en la variación ecológica da como resultado una mayor dependencia del aprendizaje individual, incluso cuando esto disminuye la aptitud promedio debido a los costos del aprendizaje, (2) La disminución del tamaño de la población aumenta la variabilidad en los tipos de estrategias de aprendizaje que usan los individuos; entre poblaciones más pequeñas, los procesos tipo deriva pueden contribuir a la aleatorización en la difusión cultural entre poblaciones, (3) Un incremento en la tasa de mutación afecta la variabilidad en los patrones de aprendizaje en diferentes tasas de variación ambiental, y (4) Un incremento en la presión de selección aumenta la dependencia del aprendizaje social. Proporcionamos un script R de código abierto para el modelo y animamos a otros a utilizarlo para probar hipótesis adicionales.

**Keywords:** innovation; technology; cultural evolution; environmental change; population structure

**Palabres clave:** innovación; tecnología; evolución cultural; cambio medioambiental; estructura de la población

> In this field of research archaeologists are in an excellent position to make major contributions to the general field of anthropology, for we can work directly in terms of correlations of the structure of artifact assemblages with rates of style change, directions of style-spread, and stability of style continuity [Binford 1962:220].

> To understand evolutionary processes, we must understand the forces that act on an ecological time scale to affect cultural variation as it is carried through time by a succession of individuals [Boyd and Richerson 1985:290].

Approximately 1,500 years ago a new technology swept through the North American Great Basin: the bow and arrow replaced the atlatl and dart as the hunting tool of choice, with corresponding changes in projectile point technology. Before the appearance of the bow and arrow, the atlatl and dart complex in the Great Basin had exhibited fairly little variation across a wide geographical expanse for thousands of years. In contrast, bow and arrow technology showed a greater degree of regional variability within a shorter period of time; points in central Nevada are more consistent in size and shape, whereas those from eastern California demonstrate considerably more variation. Bettinger and Eerkens (1999) hypothesized that the differences in form between the two regions, and within the California assemblages, derived from different ways of learning. People living in eastern California, who first adopted this technology and were only loosely connected with the bow and arrow's inventors, might have engaged in trial-and-error learning, yielding more widespread variation. When the technology arrived in central Nevada, it may have been a more fine-tuned complex, the result of success-biased learning among a more connected population; hence, the consistency observed in the archaeological record. This example highlights that success may look different among different populations but ultimately depends on the ability to create complex, ecologically relevant technologies—a process that is only possible with a cultural "ratchet." By incorporating individual inventions into existing bodies of knowledge, we can accumulate and diffuse cultural innovations, like the bow and arrow (Richerson and Boyd 2006). But how do we know when to copy others and when to learn on our own? What social and ecological contexts affect how humans choose to learn and produce innovations?

Here, we focus on the archaeological manifestations of learning processes, as seen in the invention and innovation of technology. Various terminology has been used in the archaeological literature to describe technological change. Some definitions focus on intensification, both in a general sense (technological change that increases economic productivity) and from a Boserupian perspective in which investments in increasing productivity are motivated by declining efficiency (for a review, see Morgan 2015). Others use the terms "richness" and "diversity" to theorize changes in tool form and function as they relate to subsistence patterns, population densities, and environmental conditions. We adopt Fitzhugh's (2001:128) definitions for both technological invention and innovation: "Invention is the development of a novel idea with its attendant material, practical, and informational components. . . . Innovation is the process of testing and putting into practice an invented method/device, and an innovation is an invention that has been 'tested' and is therefore no longer novel and unpracticed." By this definition invention need not entail the production of an entirely novel technology but most often reflects alterations to existing technologies. As Walsh and colleagues (2019:53) note, "Innovation occurs in and further diversifies existing material culture traditions." By looking at ecological contexts that favor individual learning to create technological diversity, and then pairing them with social contexts that promote uptake as they become innovations, we can make predictions about the circumstances that lead to cultural change. Doing so considers the historical trajectory of ideas as they reflect both the ecological and social constraints under which individuals operated in the past and in which new ideas can be generated.

Ways to test socioecological influences on the development of innovation include using experimental agent-based models and sampling case studies: in this article, we do both. This allows us to explore microscale interactions at the level of individuals and to assess the macroscale results of those interactions as influenced by outside variables. Such models are useful because the archaeological record rarely reflects microscale events, even though it is these events that ultimately shape the macroscale patterns that are evident in the record. We use an agent-based simulation to investigate how ecological variation and population size can affect cultural transmission patterns and cultural variability. Then, we infer how these learning patterns might affect the amount of variation and rate of change for cultural variants that could be acquired in these learning contexts. We discuss whether the inputs to which archaeology also has access—environmental variation and population size—may influence patterns of cultural variation, invention, innovation, and investment in new technologies over time. We encourage readers to explore the parameter settings in the R-script (Clark et al. 2023) to test additional hypotheses of the socioecological conditions for cultural evolution.

## Background

The use of artifact class and stylistic richness as measures of behavioral and cultural diversity has a long history in archaeological thought, beginning with the theoretical paradigm of culture history (see Conkey and Hastorf 1990). Viewed through the lens of culture history, variation in material culture could not be readily explained by the same processes that dictate biological change (e.g., Currie 2013). But brewing social and cultural changes in 1960s America drew archaeologists to a practice that could help analyze and explain the range of differences and similarities that constitute the human condition through an analytic and often Darwinian lens (Goodale 2019). Whereas Binford (1962:218) identified culture as an “extra-somatic means of adaptation for the human organism,” Dunnell (1980) and other early evolutionary archaeologists focused on the mechanisms driving cultural variation and the evolution of material culture. As applications of processual archaeology expanded, they broadly acknowledged the importance of environment, population density, social organization / risk sensitivity, and cultural transmission as means of driving material culture change (see Eerkens and Lipo 2007; Prentiss et al. 2021, 2023; Walsh et al. 2019).

During this time, researchers began using evolutionary-informed models to identify the learning strategies by which people acquire culture, defined as complex, accumulated, socially learned behaviors, skills, knowledge, values, and beliefs (Cavalli-Sforza et al. 1982). Because cultural information varies, can be inherited, and competes for behavioral representation, natural selection should produce cognitive structures to guide social learning toward better-choice outcomes. Accordingly, cultural evolutionists have identified several social learning mechanisms that can result in adaptive outcomes across a range of environmental and social conditions (Boyd and Richerson 1985). They predict that accuracy of learning, availability and quality of demonstrators, and costs of learning will affect how an individual finds it most efficient to learn (Kameda and Nakanishi 2002; Kendal et al. 2009; McElreath 2004; Rogers 1988). Thus, the costs and benefits of different social learning strategies are affected by the same overarching drivers of technological changes: environmental conditions and population size.

### *Environmental Variability*

In the early twentieth century, ethnographers began to focus on the geographic clustering of cultural traits, which led to an enduring tradition in American anthropology that explores the links between environment and behavior. According to Wissler (1914, 1923, 1927) and Kroeber (1939), “culture areas” represent a network of cultural traits related to the geographic range of primary food sources and their associated technologies. Although useful in concept, the approach lacked a means to identify the causal links between culture and environment and was thus unable to explore the mechanisms driving variation. Subsequent infusions of cultural (e.g., Steward 1955) and behavioral ecology (Bird and O’Connell 2006; Codding and Bird 2015) focus on economic drivers of technological change, although the development of new technologies clearly affects how people use their environments and vice versa (Morin et al. 2020; Ready and Price 2021).

Cultural evolutionists argue that it is not just static environmental factors but also the rate of environmental change that shapes pathways to innovation. As the rate of environmental change increases, individual learning is favored because information acquired previously by others is more likely to be out of date (Aoki et al. 2005; Boyd and Richerson 2005; Feldman et al. 1996; Morgan et al. 2022; O’Brien et al. 2014; Rendell et al. 2010). Alternatively, when the environment is relatively stable and the costs of individual learning are greater than imitation, natural selection should predispose people to rely on the (cheaper) information of others (Boyd and Richerson 1996; McElreath et al. 2013; Perreault et al. 2012). Morgan and coworkers (2022) replicate this pattern in an evolutionary

https://doi.org/10.1017/aaq.2023.71 Published online by Cambridge University Press

simulation that shows a drop in social learning after environmental change, followed by an uptick in social learning as the environment stabilizes.

Aspects of the environment that affect innovation include the effective temperature, length of the growing season, risk (related to changing or challenging ecologies and sometimes the colonization of new ecologies), and mobility (related to food distribution and density within a given ecological setting). For example, in a series of studies evaluating geographic variation in the North American Clovis technological tradition, Buchanan and colleagues (2014, 2016) find variation to be responsive to local environmental conditions, rather than being a result of drift. Another study of North American toolkit variation found technological richness to be negatively correlated with mean rainfall for driest month, species richness, and aboveground productivity, thereby pointing toward environmental risk as a driver of innovation (Collard et al. 2013). Similarly, Mathew and Perrault (2015) found ecology to be a stronger predictor of material culture than cultural phylogeny (although see Towner et al. [2016] for a critique of this analysis). Analysis of more contemporary populations shows the same; variation in sea craft design in the Pacific has been found to correlate both to local island environments and to the cultural histories of the people who settled there (Beheim and Bell 2011). A similar pattern is described for Thule material culture in which some elements, such as harpoon head style, evolved via cultural transmission with little responsivity to ecological variables, whereas others such as architectural features and stone tool assemblages seem to be a result of both cultural transmission and ecological context (Prentiss et al. 2018).

Explorations of technological and stylistic change related to relationships between social organization and risk sensitivity have also provided useful insights into the mechanical, operational, and strategic costs associated with innovation (Bamforth and Bleed 1997; Bousman 1993, 2005; Fitzhugh 2001; Hiscock 1994). For example, Fitzhugh (2002, 2003) describes the role of population density and sociotechnic complexity in the Kodiak archipelago where population increases coupled with pronounced seasonality appear to have driven technological innovation. Indeed, in each case, variation is best explained by using social and ecological variables together, indicating combined processes of social and individual learning, phylogenetic trends in inheritance, and context-specific constraints (or lack thereof) on technological form.

### *Population Structure*

Debate around the emergence of modern human culture prompted many to look at demographic factors, in addition to environmental variables, as a primary cause for novel and expanded toolkits. It is well established that larger populations produce more adaptive variants and are able to eliminate disadvantageous variants and promote those with an adaptive advantage more effectively (e.g., Powell 2009; Shennan 2001). It follows that small populations will exhibit more variant diversity. However, perhaps paradoxically, following the logic of neutral theory, neutral or slightly deleterious variants can potentially move quickly through small populations, and highly advantageous variants can come to fixation more quickly than in large populations (Lanfear et al. 2014; Laue 2018; Laue and Wright 2019). For example, population bottlenecks observed through population-scale Y chromosomal data coincide with periods of notable social and technological development globally (Karmin et al. 2015). These results, among many others (e.g., Shennan 2020), highlight the different evolutionary trajectories of small and large populations as driven by different rates of drift, selective conditions, and so on.

Population connectivity, not just size, should affect how people find it efficient to learn (Strassburg and Creanza 2021), and demography must matter as well. Whether populations are growing or shrinking may affect learning patterns (O'Brien et al. 2014; Premo 2016). As Binford (1962:219) noted, "Changes in the relative complexity of the sociotechnic component of an archaeological assemblage can be related to changes in the structure of the social system which they represent. Certainly, the evolutionary processes, while correlated and related, are not the same for explaining structural changes." Social milieu and local traditions also affect behavior (Camerer and Fehr 2006; Efferson et al. 2007; Henrich 2004; Wiessner 1983), and historical traditions for transmitting cultural information could hamper the response of a learning system to a change in the learning environment. In larger populations, greater proportions of individual and success-biased learners may be a contributing factor to

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greater sociocultural complexity (Carneiro 1967). Experimentally, Mesoudi and O'Brien (2008a) found that individuals prefer a success-biased learning strategy as long as costs of access to observe successful individuals are not too high.

Some empirical models that evaluate the role of population size and environmental variability in tandem have rejected population size as the primary driver of technological richness (Buchanan et al. 2016; Collard et al. 2005; Vaesen et al. 2016). One of the reasons that population size may be a poor predictor of technological complexity in the archaeological record is that effective population size should include not only local population estimates but also the total pool of learners and teachers across interacting social spheres (Shennan 2001; Strassburg and Creanza 2021). For example, Neiman (1995) suggests that intergroup transmission may have been a major driver of trait divergence in modes of lip exterior decorations in Woodland ceramic vessels from Illinois. Kline and Boyd (2010) note that in Oceania connectedness with other islands correlated with increased technological complexity, mitigating the effect of small population size and compensating for the treadmill of cultural loss through access to experts elsewhere. Of course, estimating population density and connectivity in the past is one area where gaps in our knowledge limit the accuracy of models and our attendant assumptions. Fortunately, emergent methods show great promise for reconstructing long-term population patterns (see Reese 2021).

## General Simulation of Social-Ecological Conditions and Learning Strategies

Archaeological data, cultural evolutionary models, simulations, and experiments all show that population size, selective pressures, and environment affect the incubation and spread of new cultural ideas and technologies (Derex and Boyd 2016; Derex et al. 2018; Kolodny et al. 2015). Clearly, gaps exist in our ability to understand these dynamics. These gaps are sometimes the result of patchy archaeological and environmental records, but we also often lack the ability to measure and predict complex mechanisms such as the rate of drift and selective pressures. Models enable us to explore how tweaks in these variables affect the degree and types of innovation we may expect within any specific population. To explore our predictions of cultural evolution patterns and implications for the archaeological record, we first simulate a population living in an environment that varies over time. Although simulated environments must necessarily sacrifice reality for generality, they allow us to logically test our assumptions about how the world works and to further interrogate our hypotheses and their implications as being consistent with empirical observations. We provide an agent-based simulation to explore how a population's social learning mechanisms evolve based on a variety of parameters, including the rate of environmental variation and the number of individuals people can look to when choosing someone to imitate. We use the archaeological record and previous cultural evolution models to constrain the multidimensional parameter space to investigate patterns of interest. We structured the base model around Rogers' paradox so that we could test for validity with each additional parameter setting (Rogers 1988). Curious readers are welcome to visit the github site to run basic versions of the model with just unbiased imitation (random copying) and individual learning to explore proofs of concepts; for example, increasing rates of environmental variation are correlated with higher proportions of individual learners in a society (https://github.com/matthewclark1223/MindToMatter/tree/main). We explore more complex versions later and hope others may find the simulation a useful tool for testing their own hypotheses.

In our simulation, there is one adaptive behavior for the environmental state occurring per given time period, which changes between time periods with a given probability. After birth into our population, each individual has the chance to acquire the adaptive behavior for the current environmental state. If they acquire the correct behavior, they receive a corresponding fitness benefit. After learning, each individual will be given the chance to reproduce into the next generation with a probability weighted by their fitness. Over time, the learning strategy that produces the adaptive behavior more often will increase in frequency in the population. One caveat we discuss later is that we can also set the cost of using each learning strategy (proportional to the potential benefit gained); therefore, the fitness outcomes of a particular learning strategy will depend on the cost/benefit ratio and adaptiveness to the ecological context. We can also set the accuracy of learning strategies (the proportion of time the adaptive behavior is not

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only observed but is also copied correctly to the same effect), so there is still a chance that individuals will be unable to acquire the adaptive behavior even with the best-choice strategy.

Individuals inherit a learning strategy from a parent (this is a haploid sexual model) and will be one of several types: individual learners (learn on own), unbiased social learners (randomly copy), content-biased social learners (observe a sample and copy the best), kin-biased learners (learn from parent; not included in the analysis of this article), or success-biased social learners (choose to copy weighted by the model's fitness; cf. Henrich and McElreath 2003). Before reproduction and death, individuals can act as cultural demonstrators for the population in the next generation (generations are non overlapping). We use roulette selection as a reliable model of inheritance because it works within the framework of Wright-Fisher analytical models (Zhang et al. 2008). We assume that the learning strategy phenotype is a polygenic trait in an organism with infinite loci; the phenotype depends on the inheritance of a combination of alleles at each of the loci for the learning genes.

We begin each simulation by setting up the population size and costs of learning, set any additional variables of interest (accuracy of learning, sample size of learning), and then simulate outcomes across a range of rates of environmental variation. We keep the selection pressure on learning at 20% following the average selection pressure of 16% on most quantitative traits in the wild (Kingsolver et al. 2001) and genetic moderate mutation rates at 5/1,000 replications (we also demonstrate results at 1/1,000 and 1/100 replications for context). Initial simulation begins with the frequency of individual and social learning alleles surrounding a normal distribution with a mean of 0.5 and standard deviation of 0.1, with additional results varying the starting proportions of individual and social learners. We allow each population to complete 5,000 generations and report the average for the frequency of each learning strategy from the final 200 generations.

Finally, we provide some notes on the model structure for those analytically inclined. First, almost everything in the model is adjustable, from the mutation rate to the number of generations used to calculate fitness. Necessity requires us to choose parameter settings; we report on combinations of variables that we think are of interest to our readership, although you may want to explore other settings. In an effort to limit their complexity and increase the interpretability of our model results, we make several key simplifications: (1) we test scenarios of varying population size but do not impose spatial structure on this population (discussed later); 2) we do not allow cumulative learning to occur, justifying critiques along the lines of Rogers' paradox; and (3) populations evolve through a hierarchical structure of learning strategies, allowing each to mutate and come to fixation after asking whether a previous learning strategy was more or less adaptive. This introduces a structured interdependence of the evolution of learning mechanisms that may be of interest to some (and is also modifiable to those familiar with R). Finally, although the potential to also explore a kin-biased learning mechanism is included in the code, we do not have the space to provide the analysis here. Feasibility tests of the model show that setting the learning parameters to favor any learning strategy over another does indeed lead to that strategy's success. The figures show results from varying combinations of parameter settings including (1) population size of 10–10,000 individuals, (2) rate of environmental change from 1%–60% every generation, (3) mutation rate of 1/100–1/1,000, and (4) selection pressure of 20%–40%. Baseline conditions of simulations from which we vary the parameters are as follows.

## General Simulation Results

### Increasing Environmental Variation Leads to a Greater Reliance on Individual Learning

As a baseline and test of validity, we explore a dynamic where we allow our population to evolve learning strategies across a range of rates of environmental variation. We set the parameters so that each learning bias is equally penalized (50% of the benefit of learning the adaptive behavior is sacrificed during the learning process), none is favored in terms of accuracy, and 50% of the population employs individual (versus social) learning in the first generation. Under these conditions, we observe that, as the likelihood of the environment changing between generations increases from 1% to 60%, the proportion of individual learners in the population increases, and the proportion of individuals employing all social learning strategies decreases (Figure 1). We also observe a general trend of decreased overall population fitness as the rate of environmental change is increased.

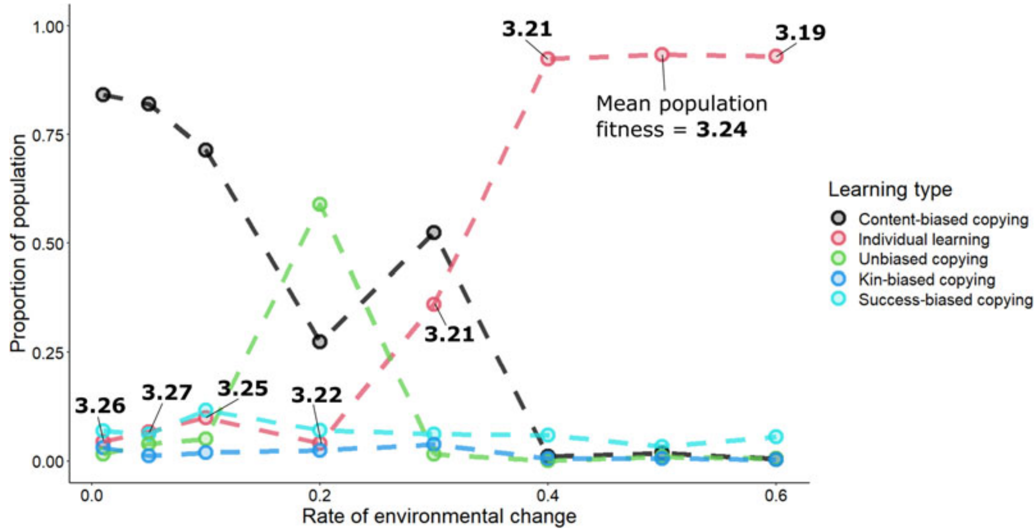


**Figure 1.** One run of the agent-based simulation. Colored lines show the proportion of the population employing each learning bias in the final 200 generations of 5,000 total. Mean population fitness across all types of learners is included along with the proportions of individual learners. The simulation parameter settings for Figure 1 are as follows: Population size = 1,000; Mutation rate = 0.005; Success rate of individual learning = 50%; Cost of evaluating content = 50%; Cost of success biased learning = 50%; Cost of random copying = 50%; Cost of kin-biased learning = 50%; Probability that success-biased learning leads to the appropriate cultural variant = 50%; Sample size of observable individuals for content-biased learning = 3; and the starting proportion of individual learners in the first generation is 0.5. (Color online)

Figure 1 shows results for conditions that favor a content-biased social learning strategy when we allow learners to sample several cultural models and choose the most effective behavior, with a sample size of three. Using a smaller sample size than three cultural models made the content-biased learning strategy too ineffective to evolve, and a sample size larger than three did not increase the fitness of content-biased social learners. However, this bias can continue to outperform individual learners, even at higher rates of environmental change, if it starts in the majority. Yet, there are many conditions produced in these simulations that result in no clear winner for learning strategies. Any learning bias that is set to be cheaper (and more accurate) evolved to fixation because the costs of the learning bias affect an individual's likelihood of reproduction. These costs may vary by the thing to be learned or the social situation of the learner, further producing variability to be explored in the future.

### *Increasing Population Size Decreases Variability in the Mixes of Social Learners*

Across populations of 10, 100, 1,000, and 10,000 we can observe decreasing variability in the proportions of individual learners and unbiased imitators (Figure 2). As population size increases, clear trends in selection for learning types emerge at different rates of environmental change. Smaller archaeological populations may have more randomness in the types of social learning that people use (not just the traits they have available to copy), with drift-like processes affecting how people may learn new technology; these processes then affect the nature of technological evolution. We ran the simulation 10 times at each population size.

### *Increasing the Mutation Rate Has a Similar Effect to Increasing Population Size*

We allowed for more extreme mutation rates of 1/1,000 and 1/100 compared to our baseline of 5/1,000. Under the reduced mutation rate (1/1,000), we see reduced variation in learning strategies that emerge at lower levels of environmental variation, indicating that there is not enough variation in the population for selection to find the optimal strategy. Additionally, compared to when the mutation rate is very high (1/100), we observe a more marked shift from biased social learning to individual learning as the rate of environmental change increases, using the intermediate, baseline mutation rate. Instead, under the high mutation rate, we observe that intermediate rates of environmental change drive the

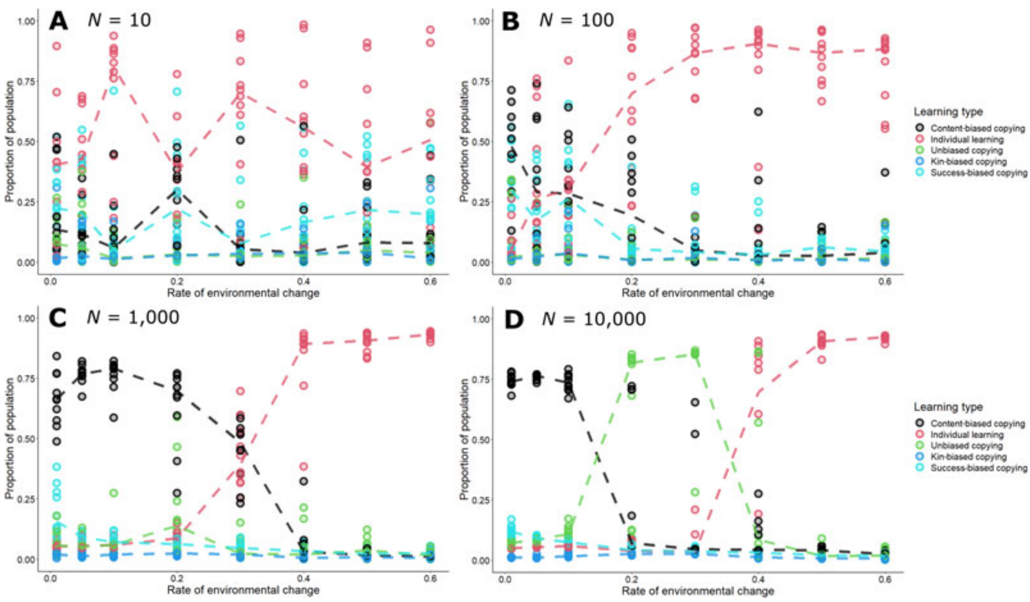


**Figure 2.** Ten runs of the simulation at each rate of environmental variation across a range of population sizes from 10 to 1,000 individuals. Simulation parameters are the same as for Figure 1, with the exception of population size. Dashed lines show median trends in proportion of different learning strategies. (Color online)

evolution of an unbiased imitation learning strategy (Figure 3). Again, we ran the simulation 10 times at each level of environmental variation.

## Case Study: Adoption of the Bow and Arrow in the American West

Given archaeologists' interest in leveraging agent-based models to explore past phenomena, we return to the bow and arrow case study and use our model to test the underlying assumptions of the Bettinger and Eerkins (1999) scenario. To restate, Bettinger and Eerkins hypothesize that the variability in arrow form observed between eastern California and central Nevada is the result of two different forms of knowledge transmission—a direct or content bias learning involving trial and error, and an indirect bias to copy successful individuals, instead of traits—each driven by underlying population dynamics. We extrapolate values for eastern California and central Nevada (Figure 4) prehistoric population density and environmental variability, as described later, to set the starting parameters for our model and to explore how environmental and population differences lead to forms of cultural transmission that could manifest differences in tool form observed in the archaeological record.

Population estimates for eastern California are derived from Steward (1933, 1938) and recent deep-time population constructions for the Owens Valley, the western Sierra, and Deep Springs areas (Eerkens 2003; Polson 2009). These sources place population densities at 0.17–0.34 persons per km$^2$ during ethnographic times, and 0.08–0.16 persons per km$^2$ at approximately 1500 BP. The total population at 1500 BP was likely somewhere between 1,000 and 1,500 individuals. Annual precipitation for the Owens Valley, the western Sierra, and Deep Springs as reported by Eerkens (2003) averaged 25.9 cm. Broader precipitation trends for Inyo and Mono Counties, California, from 1900 to the present record annual rainfall at 15.5 cm for Inyo County and 39 cm for Mono County (National Centers for Environmental Information, https://www.ncei.noaa.gov/pub/data/cirs/climdiv/). Together, modern annual precipitation calculations across the areas of interest amount to an average of 26.8 cm annually. Deep-time environmental reconstructions for the Owens Valley and Mono Lake areas show peaks in aridity and low lake stands from 2500–1800 cal BP (Mensing et al. 2013, 2023; Stine 1990) preceding the uptake of bow and arrow technology. Termed the Late Holocene Dry period (LHDP), this mega-drought appears to have been more pronounced in central and southern Nevada than in northern Nevada and outside the Great Basin generally. We cannot know with certainty the pace of climate change

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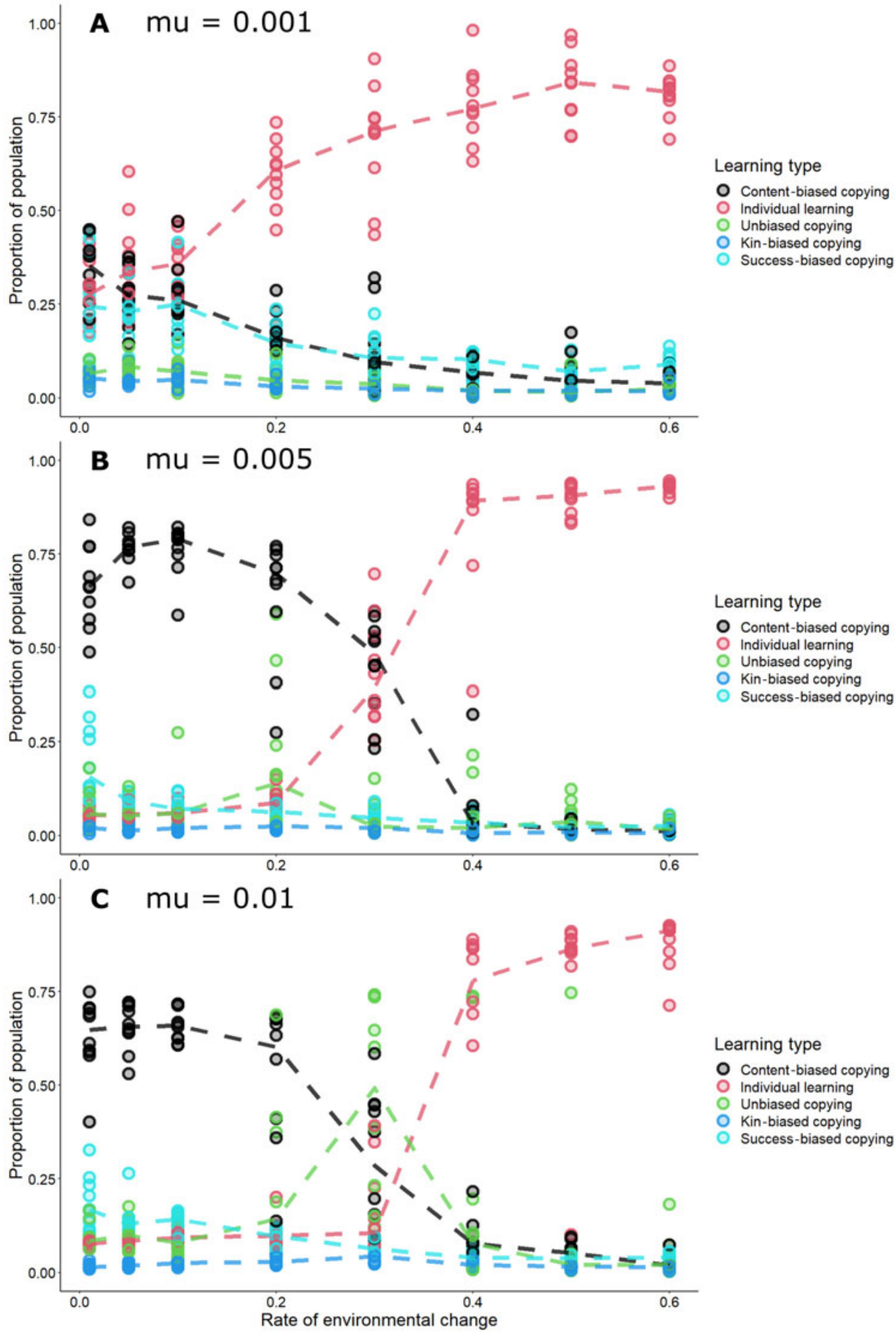


**Figure 3.** Ten runs of the agent-based simulation for each of three mutation rates. Colored lines show the proportion of the population employing each learning bias in the final 200 generations of 5,000 total for each of the 10 runs. Dashed lines show the median proportion of the population employing each learning bias across the 10 runs. The simulation parameter settings are identical to those shown in Figure 1, with the exception of the mutation rate. (Color online)

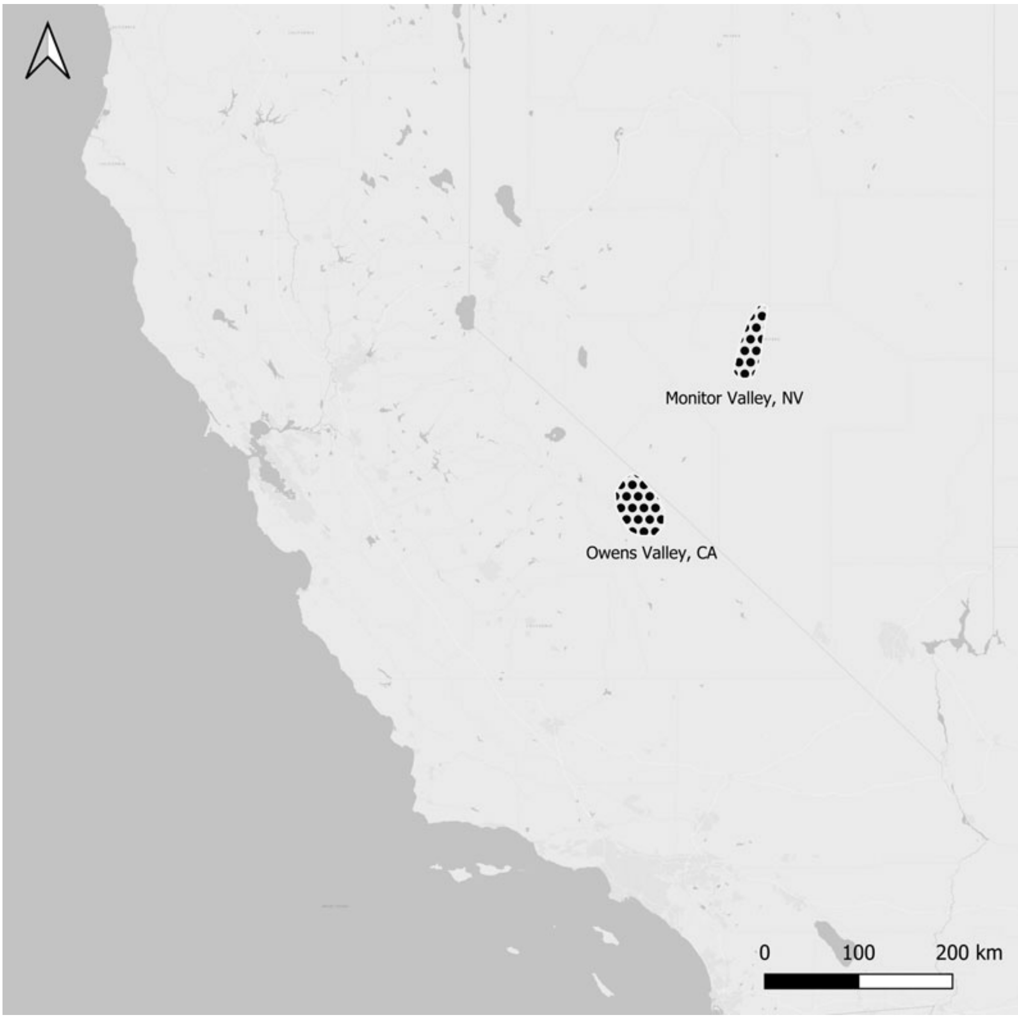


**Figure 4.** Locations of source assemblages examined in Bettinger and Eerkens (1999); central Nevada including Monitor Valley and eastern California including Owens Valley, California.

after the LHDP; however, a wetter period did follow, although the overall trend toward increasing aridity persisted through about 500 cal BP. Thus, we expect precipitation in eastern California to have been lower during the period of bow and arrow adoption, though how much lower is difficult to infer.

Population density for central Nevada, again derived from Steward (1938), ranged from 0.12 to 0.11 persons per km$^2$ in ethnographic times. Population reconstructions, as have been done for Owens Valley, are not available for this region. However, for the purpose of our model, we need not calculate exact population numbers but rather note that the population in central Nevada was likely significantly smaller, perhaps by as much as half, than that in eastern California. Under this assumption we estimate a low value of between 500 and 750 individuals, though that number may have been even smaller. The Monitor Valley and surrounding areas also experienced the LHDP megadrought described earlier, and possibly to a greater extent than did the Owens Valley (Mensing et al. 2023). Recent climate reconstructions for the alpine villages of Alta Toquima and nearby Dakabah, which are adjacent to Monitor Valley, demonstrate past variability. Inferred projections for past millennial fluctuations suggest warmest/cold intervals ranging from +2°C to −2°C relative to mid-twentieth-century means (Millar et al. 2019; Thomas 2020). Modern precipitation trends for Nye County, Nevada (1900 to present), average 20 cm total precipitation annually (https://www.ncei.noaa.gov/pub/data/cirs/climdiv/).

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Given the severity of the LHDP, we expect that there was likely less precipitation in this area during the period of bow and arrow adoption.

We use these data to derive parameter settings for the model. First, we begin with a low-number population estimate of 500, which is representative of the central Nevada population. We run the model across populations up to 2,500 people in size (an estimate higher than any projected for precontact populations). We then run the model across a range of environmental conditions with the likelihood of environmental change between generations ranging from 1% to 50%. We assume a moderate mutation rate at 5/1,000 replications in each sweep. We model selection pressure at 20% and 60%.

### Results

#### Lower Rates of Environmental Change Promote Social Learning, and Higher Rates Push Individual Learning

When we simulate across a range of conditions of increasing environmental variation and population (averaging across 10 runs of the simulation), we observe that environmental variation has a much stronger effect on the percentage of individuals who use individual learning (Figure 5). At low rates of environmental change, almost everyone in the population, regardless of size, uses social learning; at high rates of change, they use individual learning. We calculate the proportion of social learners to include all types of social learning.

#### Increasing Selection Pressure Increases the Proportion of Social Learners in the Population

When we run the same set of simulations while increasing the selection pressure of learning the adaptive behavior for the environment from 20% to 60%, we see an increase in the proportion of social learners in the population (Figure 5). Only at very low and very high rates of environmental variation, and for smaller population sizes, do we see the dichotomy produced in populations with the more moderate rate of selection pressure.

## Discussion

Binford (1962:220), among others, highlights the role of in situ sociocultural dynamics in technological innovation and spread: "Changes in the temporal-spatial distribution of style types are believed to be related to changes in the structure of sociocultural systems either brought about through processes of in situ evolution, or by changes in the cultural environment to which local sociocultural systems are adapted, thereby initiating evolutionary change." Our results mirror these observations, demonstrating that environmental variation, population size, and changing mixes of learning styles affect from whom people find it efficient to learn, thus affecting innovation and cultural evolution.

Some of our results bolster what we already know about innovation; for instance, that environmental variation affects the frequency of individual learning and that the costs and accuracies of learning biases can override socioecological factors. When individual learning is both costly and inaccurate, individuals rely on social learning. Other results highlight forces of evolution that go beyond selective pressures, such as drift-like processes in small populations that may result in diverse outcomes in preferred learning strategies, which then may affect patterns of cultural evolution. That starting conditions can create inertia on resulting social learning patterns is a unique finding and one that archaeological data may be particularly suited to address.

Regarding the uptake of bow and arrow technology in eastern California and central Nevada, our results provide an interesting counter to previous investigations. Both our general simulation results and our bow and arrow specific sweeps demonstrate that, in locations with low environmental variability, social learning should be the predominant strategy because it will likely result in less variability; conversely, when environmental variation is high, individual learning should be favored. But this is not what we see in the archaeological record. Eastern California, which had higher population densities and presumably slightly less environmental variation at the time of bow and arrow adoption, has more varied arrow technology, whereas the reverse is true of central Nevada.

We propose several hypotheses to explain these results. First, perhaps the archaeological record reflects what has been demonstrated in other modeling exercises (Laue 2018), which is that highly

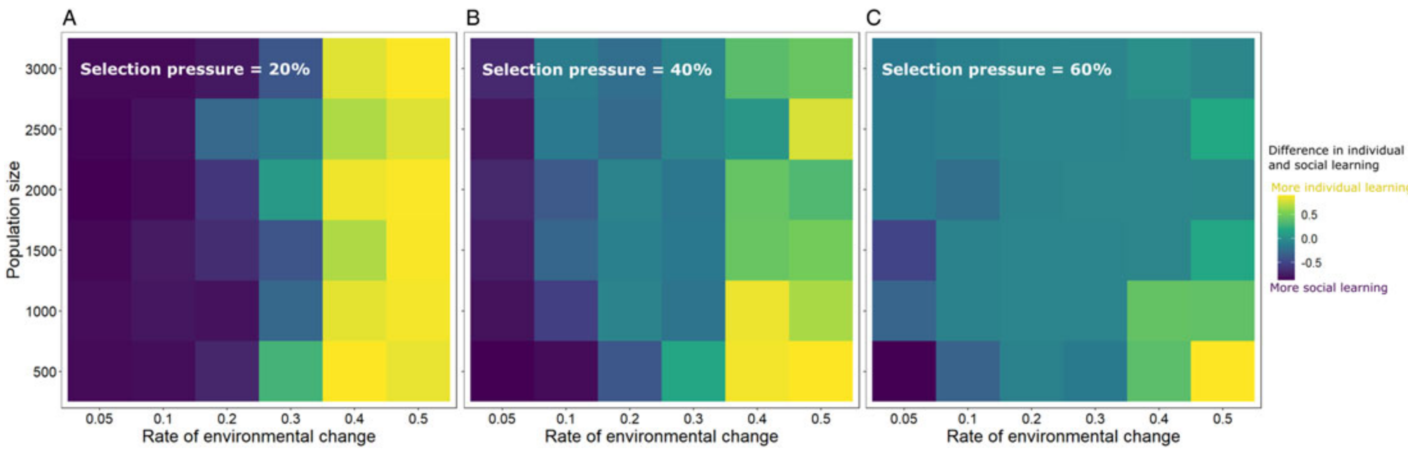


**Figure 5.** Heat maps of 10 runs of the simulation across different combinations of rates of environmental variation and population sizes, for three selection pressures: (A) 20% selection pressure, as was used for previous results; (B) 40% selection pressure; and (C) 60% selection pressure. Darker cells indicate a higher proportion of all types of social learners; lighter cells indicate higher proportions of individual learners. (Color online)

https://doi.org/10.1017/aaq.2023.71 Published online by Cambridge University Press

adaptive traits can come to fixation quickly in small populations. If this is the case in central Nevada, individual experimentation would be difficult to detect archaeologically because the best arrow form would have come to fixation rather quickly. The archaeological outcomes may thus look quite similar to those produced by a social-learning-like pattern. Alternatively, both eastern California and central Nevada populations may have been experiencing mid-range environmental variation. This produces flux in preferred learning strategies as individuals shift back and forth between social and individual learning, regardless of population size. It is feasible that in some locales the archaeological expression of this flux will appear more like social learning, whereas while in others it will appear more like individual learning. A third possibility is that we overestimated the population size of central Nevada. Modeling very small populations might result in an even more pronounced role for drift; this may result in variability not only in the traits that come to fixation but also in the learning patterns that drive variation. Finally, it is possible that eastern California experienced a greater degree of environmental variability than is recognized in existing paleoclimatic records. If so, that population may have shifted to an individual learning strategy, resulting in variation in technological traits, which exemplifies the observed pattern. This scenario does not, however, provide any resolution for the central Nevada pattern.

What is more likely is that selection pressures were very different for the different populations and that these selection pressures shaped the adoption of varied arrow technologies. We demonstrate this in our case study model sweeps; when we increase selection pressure, we see an increased reliance on social learning across almost all conditions (see Figure 5). It may be that, while experiencing a megadrought, populations in Nevada experienced higher selection pressure to get the technology right, which led to less individual experimentation and more selective copying. In their own simulation, Premo and Kuhn (2010) also see reduced variation in culturally learned behavior with higher local group extinction rates when individuals rely on social learning. In any case, what is clear is that the model provides archaeologists an opportunity to test assumptions about the drivers of technological change and to generate new hypotheses about that change based on model outcomes.

Future research should also consider the processes by which the use of social learning biases is itself subject to learning (Greenbaum et al. 2019; Mesoudi 2011). Across the ethnographic record, children tend to learn from kin while young and then update their knowledge through experience and learn from interactions with non-kin as they mature past puberty (Aunger 2000; Demps et al. 2012; MacDonald 2007). But there is a great deal of variation in this general pattern because subsistence systems tied to local ecologies can affect community interdependence, reliance on social learning, and from whom kids learn how to learn (Glowacki and Molleman 2017). Changing ecological and social environments may affect patterns of children's acculturation and invention differently than in adults and from whom they have access to learn and to teach (Lew-Levy et al. 2020). Errors that arise through children's sampling and application of learned behaviors can contribute to the happy accidents of invention and innovation. Cognitive processes beyond those we have modeled, such as intense emotional experiences, can affect social learning as well (Fogarty et al. 2015).

But the coarseness of much archaeological data means that we do not typically observe these individual acts of invention in the record; rather, what is "seen" are the last steps of the innovation process, namely widespread adoption (Schiffer 2010; Sterelny 2020). Our ability to disambiguate time-averaging effects is ultimately tied to archaeological sample size and the ability to detect and measure artifact richness/diversity over time and across different sets of users (Jones et al. 1983; Premo 2014). Much has been made over how to interpret the palimpsest-like nature of the archaeological record (for a review see Holdaway and Wandsnider 2008). Then, too, there is also the problem of underdetermination, leaving us unable to discriminate among the processes that may have created a set of observations (Perrault 2019). The model presented here will likely generate outcomes that "go beyond the data."

Future simulation efforts to better emulate past human learning contexts should be open to additional social learning biases; for example, we neglect conformity, similarity, and prestige. Prestige and conformity learning biases have been shown to drive variation in artifact assemblages (Bentley and Shennan 2003; Kohler et al. 2004; Shennan and Wilkinson 2001), although lab simulations suggest that people might not use prestige-biased learning when responding to environmental shifts (Atkisson et al. 2012). We also lumped the costs of learning into one parameter: there is no difference

https://doi.org/10.1017/aaq.2023.71 Published online by Cambridge University Press

between the time it takes to learn something versus the resources spent accessing a high-quality demonstrator. As Boyd and Richerson have shown (1985), identifying and accessing a demonstrator can cause runaway processes on the traits involved that are not investigated here. These will certainly affect trade-offs in learning differently than opportunity costs and influence how inventions may arise and spread. The other major simplification we made here was to ignore the fitness landscape of material culture. In simulated environments with one best technological solution—for example, the case of projectile point design—individual learning was the most effective mechanism to achieve the global optimum of point design (Mesoudi and O'Brien 2008a). But the same simulations run in environments with several best-choice technologies at spatially distributed local optima demonstrate that copying a successful neighbor was the most efficient way to get the best technology (Mesoudi and O'Brien 2008b). Although our model can help make predictions regarding responsivity to climate-driven sociocultural change, these results continue to lead us to more questions. Should we expect technological shifts to align with the onset of climatic events, or rather should we expect to see lags in the archaeological record relative to major climatic change (e.g., Kelly et al. 2013)? Of course, predictions may differ for functional versus stylistic traits, as well as for traits that are selectively neutral (Neiman 1995).

Finally, several technological investment models focused on archaeological applications consider the cost of research, development, and accuracy in replication (for a review, see Herzog and Goodale 2019). What, if anything, should a model consider in regard to these constraints, and how? As noted by Bettinger and colleagues (1996:137), "It pays to retain a suboptimal tool when searching for the optimal alternative is costly or error prone (Boyd and Richerson 1992; Heiner 1983; Simon 1959)." A similar problem is addressed by the technological investment model proposed by Stevens and McElreath (2015) in which they consider when investment in two specialized tools is better than investing only in one generalized tool. Although no model could, or should, discuss all possibilities, we look forward to a future with a more collaborative understanding of simulation, experimentation, and excavation to understand the variation in innovative processes.

## Conclusion

Although the implications of the Bettinger and Eerkens model have been largely accepted as explaining projectile point variation in the late Archaic Great Basin, the factors driving patterns of innovation, such as population structure, selection pressure, and the extent of environmental flux necessary to drive the trends, need further investigation. Models, like the one presented here, provide us with new ways to think about complex phenomena such as technological innovation. If one hopes to use conceptual models to better understand the archaeological record or, indeed, any record of cultural change, it is necessary to control for the influence of factors such as environmental context/variability and social organization. Each factor alone, and especially in combination, shapes the world of what is possible, the adaptive landscape, and the personal and population incentives. We encourage readers to use the simulation code provided to explore their own hypotheses for the ecologies of social learning.

**Acknowledgments.** Thanks to Parry Martin Rhys Clarke and Richard McElreath for their guidance in setting up the original R script for this project. We also thank Kyle Shannon for assistance in using the Boise State Research Computing array.

**Funding Statement.** Boise State University College of Arts and Sciences provided funding for a writing workshop to complete this manuscript.

**Data Availability Statement.** R code is available at Clark and colleagues (2023).

**Competing Interests.** The authors declare none.

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**Cite this article:** Demps, Kathryn, Nicole M. Herzog, and Matt Clark. 2024. From Mind to Matter: Patterns of Innovation in the Archaeological Record and the Ecology of Social Learning. *American Antiquity* **89**(1):19–36. https://doi.org/10.1017/aaq.2023.71.