Chapter 15
Human Behavioral Ecology and Technological Decision-Making

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Introduction to Human Behavioral Ecology as a Theoretical Framework

Within the HBE framework, optimal foraging theory (Emlen 1966; MacArthur and Pianka 1966) is the most common lens through which archaeologists work. The classic model, termed "encounter-contingent prey choice" or "diet-breadth" model, was developed by evolutionary biologists (Stephens and Krebs 1986; Pyke et al. 1977; Charnov 1976a) to identify which types of prey one would expect to be included in the diet. In this subsistence-based model, the individual forager's goal is to maximize net rate of energy intake given the set of resources available. Foraging decisions are distilled into simple yes/no choices that depend upon the profitability of the object at hand vs. the assumed net rate of return achieved by passing up the resource to continue the search for something else. The profitability of a given resource is calculated by quantifying its energetic content (kcals) and then dividing that by the amount of time spent handling (i.e., harvesting, butchering, grinding, cooking) the resource to convert it into an edible product. The expectation is that a forager should decide to pursue a resource when encountered if the profitability of that resource is greater than the anticipated net rate of foraging return per unit foraging time.

The prey choice model can be expanded to examine patchily distributed resources as well (MacArthur and Pianka 1966). Within the "patch choice" model, the decision variable becomes, should one enter a patch, and if so, how long should one stay. Thereby, patches themselves enter and fall from the diet based on the average return across all available patches. In a given patch, profitabilities will fall based on time spent in exploitation, a phenomenon formally modeled by the marginal value theorem (MVT; Charnov 1976b). MVT describes the amount of time a forager should spend in a particular patch before moving to another. The decision for a forager is how much of the resource to take and how long to stay in each patch. Trade-offs are made between time spent in the patch and time spent traveling between patches. In accordance, "One would expect a forager's patch-leaving behavior to reflect a balance between the diminishing returns of patch gain and the value of the forager's options elsewhere" (Stephens 2008, p. 475). MVT predicts behavior based on diminishing returns, a common occurrence in natural systems, something humans are cognitively aware of, and

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a concept which has proven to be an invaluable tool in the study of human decision-making across many aspects of behavior both past and present (Bettinger and Grote 2016).

While the optimal foraging model, MVT, and others center on subsistence, these same models have been recast by archaeologists to focus on a broad range of subsistence-related problems such as central place foraging (e.g., Metcalfe and Barlow 1992), the origins and spread of agriculture (e.g., Barlow 2002; Kennett and Winterhalder 2006), and the sexual division of labor (e.g., Elston and Zeanah 2002). Archaeologists have used these models to explore problems in prehistory for the past four decades, leading to a comprehensive body of literature (for reviews see Broughton and O'Connell 1999; Bird and O'Connell 2006; Codding and Bird, 2015). Here, we turn to a set of optimality models that focus specifically on the procurement, manufacture, and use of primitive technologies. Using the same cost/benefit logic of the optimal foraging tradition, these models explore variables related to tool manufacture and use including raw material extraction, transport and processing, tool construction and maintenance, and use and service life. The models are also useful in explaining technological changes from simple/expedient to complex/costlier tools.

Constraints on Technological Decision-Making and Design

Variation in technological systems involves complicated interactions between human decision-making with relationship to raw material availability, raw material quality, and the ratio of producers to consumers (Goodale et al. 2008). Tool categories that make up technological systems are often considered to be systematic, meaning close to uniform in size, shape, weight, or any other functional attributes, or unsystematic, meaning highly variable (Bleed 2001; Brantingham et al. 2000), but can usually be described along a continuum of uniformity (Shott 1996). The use of technology incorporates both the procurement of resources, which may be modeled within an HBE framework (Surovell 2009), and the relative skill (Bleed 2008) of the producers, which may be better understood through evolutionary frameworks such as dual inheritance theory (Chap. 3; Boyd and Richerson 1985; Shennan 2002). For example, there is an interesting debate surrounding the maintenance of complex technologies and whether they are driven by imitation or are the result of adaptive change in response to subsistence shifts (Henrich 2004; Read 2006). However, here, we concentrate on HBE frameworks and begin with the fundamental principle of optimality in technological decision-making.

Technological systems are composed of design features that have the potential to be converted into individual reproductive success, and thus, natural selection can have the consequence of optimizing design features. When portions of technological systems are under selection because they optimize somatic interests (increase access to resources), technology can contribute to an individual's reproductive success (Krebs and Davies 1997; Smith and Winterhalder 1992). In circumstances where resource access is competitive and there is variation in the strategies to solve for a particular goal, natural selection should favor the strategy that solves the problem with a least-cost path over other strategies that may be available (Foley 1985). The reason for natural selection to favor the least cost decision is that humans have limited energetic budgets. Those individuals that can save energy while at the same time solve particular problems that optimize their somatic interests can convert energetic surpluses into other endeavors that also increase reproductive success (Kaplan et al. 2000). Based on this argument, one might draw the conclusion that humans are designed to optimally adapt to their environment because of technological decision-making. Alternatively, the conclusion to be drawn from this line of reasoning is that natural selection tends toward the optimal solution given a range of available solutions present in the environment (Foley 1985; Smith and Winterhalder 1992). There is also contingency from their evolutionary history as decision-making occurs through time (Prentiss and Clarke 2008).

Human decision-making can be described as behavior that is behaviorally and cognitively flexible or plastic (Flinn 2005). Plasticity allows humans to respond to fluctuating social and ecological selection pressures. Over time, technological decision-making will tend toward optimizing the net return rate in relation to the energy invested. Concurrently, humans are aware of diminishing returns that may be associated with particular decisions in problem-solving. This allows humans to adjust investments according to optimal return rates (Kaplan and Lancaster 2000; Smith 2000).

The degree of optimization is dependent on the selection pressures associated with a particular resource (Foley 1985) and the technology used to procure the resource. When a resource has a high impact on fitness (high contribution toward reproductive or other somatic interests), individuals who focus attention on procuring that resource can achieve greater fitness (Hames 1992; Winterhalder 1983) and are also likely to invest in the technology used to procure the resource. If the opportunity exists to increase fitness through procuring a resource, optimal strategies will outcompete other strategies. Alternatively, if a resource has low impact on fitness, optimization may not occur, but it is more likely that satisfactory solutions for obtaining resources with low selective pressures will be viable and variation in the ways of completing a task will be tolerated. Winterhalder (1983) provides a model demonstrating the circumstances that would favor decisions to invest an additional unit of time and energy into a specific activity (conditions of limited energy) or to cause limited resources into other activities (conditions of limited time).

For human populations that rely on technology for access to food or other interests, the nature and access of technology impacts reproductive success. Raw materials used to create technology, in many cases, approximate a zero-sum game. In other words, when one individual accesses raw materials used to make technology, it represents a loss for other individuals in a population. When raw materials are proportionally high compared to a hypothetical population, the depletion of raw materials may be inconsequential to everyone. Therefore, access to raw materials to produce technology may have low fitness consequences, as there is likely little competition in procurement. When available raw materials for producing technology are proportionally low compared to demand, competition in procuring those resources will likely be high.

Under optimality reasoning, one would conclude that when use of raw materials to produce technology is highly competitive, strategies for converting the raw materials into usable technology will be constrained with the likely solution (or solutions) being those that are most economical given the range of possible solutions present. An outcome could be that only a few individuals might specialize in production from a limited resource, with others opting to consume the other resource types that are available (Nakahashi and Feldman 2014). If a resource is quickly being depleted, individuals may obtain a better payoff by redirecting their time and energy into other goals that increase fitness or other interests. Reasons for this are that when there are constraints on resource availability, not everyone can effectively engage in a specific economic pursuit (i.e., technological production), and the range of strategies employed may be more broad. On the other hand, when raw materials are under low selection pressure, access to them is unlikely to have a negative impact on other people using the raw materials. In this case, more people will be likely to act as both producers and consumers (engaged in producing technology as well as using the products).

Modeling Technological Variation: Raw Material Availability, Quality, and Ratio of Producers to Consumers

Variability in technology is a likely result of human decision-making in relation to raw material availability, quality, and the ratio of producers to consumers. Investments in technology vary both spatially and temporally (e.g., Beck et al. 2002; Bleed 2008; Prentiss et al. 2015; Surovell 2009), and the links between raw material availability (Beck et al. 2002; Kuhn 1996) and quality (Andrefsky

1994; Brantingham et al. 2000; Kuhn 1996; Surovell 2009) on the constraints of technological design and conformity have been made in a number of studies. More specifically, Surovell (2009) provides a mathematical model to examine the differing transport costs of lithic cores and tool blanks within Paleoindian contexts of North America. Following Kuhn (1996), the model as Surovell (2009) presents it is applicable as a general model of decision-making with regard to the question of when to transport cores versus tool blanks. Raw material availability can be modeled in HBE terms as the kcal/hour expended to procure and transport the resource. This takes into account the distance one has to travel to procure the raw materials and package size/weight that has to be carried (Beck et al. 2002). Goodale et al. (2008) model variation in technology as increasing at the square root of availability. Where variation increases drastically with changes in low availability, the slope becomes less extreme as availability approaches maximum (total availability equates to easy access and travel time/distance is short). This is similar to Surovell's (2009) model which is tested explicitly against the archaeological records of a number of Paleoindian sites in North America.

Raw material quality relates to the composition of the resource and also how easily it is converted/manipulated to be used as technology. As one may imagine, raw material quality could be described in a number of ways depending on the material's composition. For stone to be converted into technology, one might describe quality as the homogeneity, percent impurities, crystal size, or anything that relates to the fracture mechanics of the material. In other technological instances, such as ceramic production, quality might relate to clay grain size and mineralogical make up as well as what temper needed to be added to produce vessels that function as intended by the maker.

Goodale et al. (2008) present a graphical model to illustrate the relationship between raw material availability, quality, and the ratio of producers to consumers (Fig. 15.1). The model was developed for examining variation in stone tool core reduction strategies but is more widely applicable across technological systems (Goodale and Andrefsky 2015). Goodale et al. (2008) model variation in technology as it relates to quality as a decaying exponential. Here, variation (v) is proportional to the ratio of producers to consumers (μ), the square root of availability (a), and the base of the natural logarithms ($e \approx 2.718$), to the negative power of α times quality (q).

$$v\,(a, q, \mu) \propto \mu\sqrt{a}\; e^{-\alpha q} \tag{15.1}$$

From this perspective, variation in technology is highest when the quality of raw materials is lowest, and variation in technology is lowest when raw material quality is highest. There is the further expectation that at low quality, variation increases rapidly but when quality increases, variation does not change nearly as rapidly. In reality, this simplified relationship is probably much more complicated and based on a number of variables that would be difficult to model in mathematical terms. However, as a main goal of HBE is to generate predictive models to provide a set of expected outcomes under circumstances of optimization, not every case may meet all predictions. In this circumstance, the link between technological variation and the ratio of producers to consumers may be more complicated than a simple linear relationship (as the ratio of producers to consumers approaches 1:1, variation will constantly increase).

General models that attempt to ask questions regarding the ratio of producers to consumers in a given cultural and geographic context can help test hypotheses about the nature of human behavior and lithic technological organization (Bleed 2008; Goodale et al. 2008, 2015; Prentiss et al. 2015). While many of these models have yet to be applied to other technologies and their constraints, the variables within are at the core of the debate around the rise of social transitions such as craft specialization (Costin 1991). As demonstrated above, the constraints on technological decision-making and resulting diversity of outcomes are complexly related with raw material, the number of people engaged in technological decision-making, and selective pressures (or lack thereof). Future applications will no

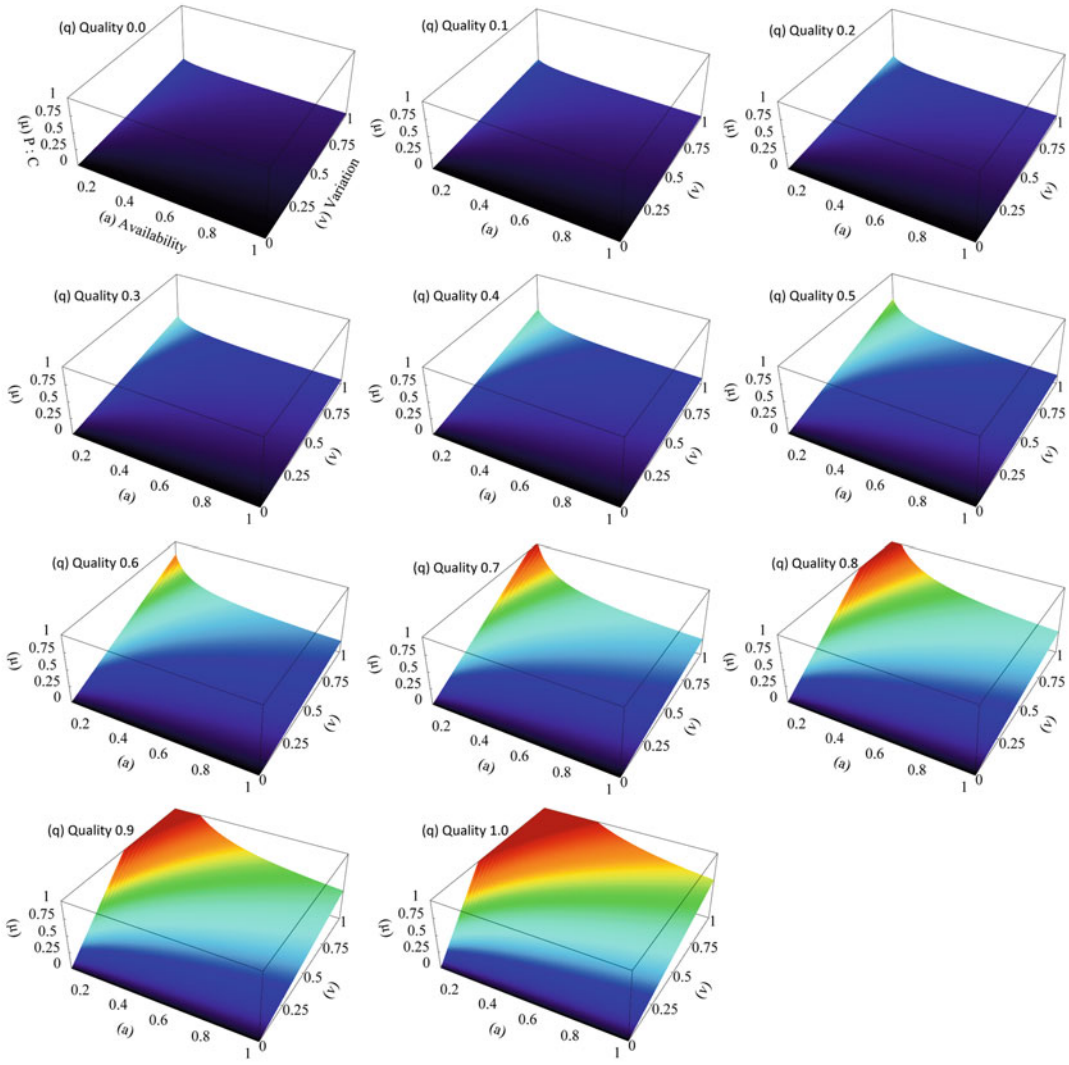


Fig. 15.1 Graphic model of Eq. (15.1) representing the relationship between raw material availability, technological variation, and the ratio of producers to consumers sequentially scaled to increase in raw material quality (Goodale et al. 2008). The mathematical relationships for availability, ratio of producers to consumers, and technological variation are along the X, Y, and Z axes and raw material quality changes in increments of 0.1 (on a scale of 0, lowest quality, and 1, highest quality)

doubt tackle these complicated problems, and the developed set of models outlined here will serve as a sound foundation in addressing the questions of what to produce and how. We now turn to the questions: when and why do people invest in technology?

Constraints on Technological Investment

In an early ethnographic application of the prey choice model among living hunter gatherers, Hawkes and O'Connell (1992) noted that shifts in the amount of time dedicated to search (looking for a resource) vs. handling (pursuit of identified resource, collection, and preparation for consumption)

have implications for subsistence transitions. As diets become more broad, rate maximization is constrained because search time has already been greatly reduced, leaving only costs associated with handling to vary. Under these conditions they note, "innovations that increase handling efficiency [tools/technology] will have their greatest effect. In fact, investments in handling improvements will be the *only* way to achieve higher food-acquisition rates." (Hawkes and O'Connell 1992, p. 64). If increased investments in search offer no better returns, populations may tend toward sedentism, at which point we should expect "technological intensification" to follow.

Archaeologists have also noted the links between increasing sedentism and increasingly specialized toolkits (for a review see Morgan, 2014). Drawing on these observations, models of technological innovation aim to provide a mathematical framework from which to evaluate how and why certain technologies evolve. Much like the prey choice model, technological investment models are contingent on optimization; does an investment now provide a higher benefit than forgoing such investment in favor of the existing toolkit? This of course depends on the continued success of the current set of tools and also the structure of the resources available. If conditions change such that the current strategy no longer provides adequate return, an investment in an alternative strategy may provide a higher return despite high initial costs. It should be noted that while expensive technology does make the process of food procurement more efficient, this efficiency should not be confused with improved subsistence efficiency—on the contrary, intensification, as it relates to technological refinement, is often associated with *declines* in overall subsistence efficiency (Bird and O'Connell 2006, p. 153).

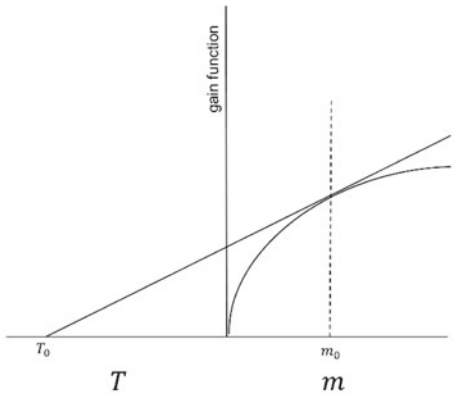
Efforts to evaluate these processes from an optimization approach have been common, but an explicit use of the theoretical framework of HBE less so. One early application of an explicitly HBE technological investment model to an archaeological dataset was published in 2002 (Bright et al. 2002). This paper examines various technological forms (milling stones, ceramic, and flaked stone tools) as they relate to the archaeofaunal record of the late prehistoric era in Little Boulder Basin, north-central Great Basin. A formal treatment of the model was presented in a theoretically driven companion piece published the following year (Ugan et al. 2003). We begin our review of technological investment models with this and a second set of HBE tech models (Bettinger et al. 2006; Bettinger et al. 2015) and then examine subsequent iterations and applications.

Two Theory-Driven Technological Investment Models

Investment as the Decision: When to Invest and When to Stay Simple

In the 2003 piece titled, "When is Technology worth the Trouble", Ugan et al. (2003) outline several technological investment models that articulate the relationship between handling time as a function of time invested in tool manufacture. Here we focus on the variant applied by Bright et al. (2002); it builds on the classic prey model by replacing the yes/no food pursuit decision variable with a yes/no decision regarding investment in a given technology. The model defines the following problem: in order to improve the profitability of a specific resource, a forager must expend some energy improving the processing tools available to handle that resource; when should the forager decide to invest energy in the manufacture and maintenance of processing tools?

The goal of the model is to predict the optimal amount of time to invest in tool manufacture as a product of three variables (see Box 15.1): (1) total time spent in search, (2) encounters with resources, and (3) base handling times for resources (the more handling time a resource requires, the more time should be invested in developing and maintaining associated processing technologies). The currency stipulated in the model is return rate measured as kcals/time.

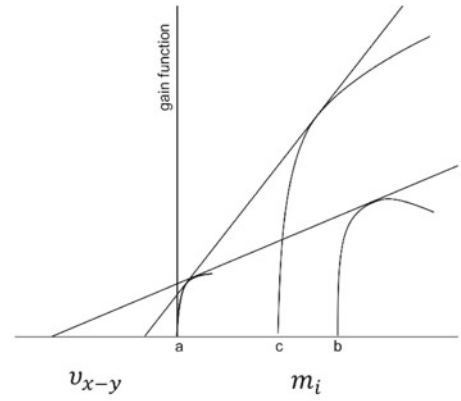


The Ugan et al. (2003) model predicts the optimal time investment in a given technology.

$f'(m) = \frac{f(m)}{m+T}$ gain function

m time invested in manufacturing technology

m_0 point at which gains are maximized over time spent



The Bettinger et al. (2006) curve-estimate model predicts the critical use threshold for determining when to switch to a different technology.

$f_i(m_i)$ gain function

m_i time invested in manufacturing technology

v_{x-y} critical threshold for switching

a—c marginal gains curve for three technologies

Box 15.1 Graphical representations of the Ugan et al. (2003) and Bettinger et al. (2006) technological investment models

Like all models, the Ugan et al. (2003) model makes several assumptions regarding past behavior. The first is a time allocation problem in that time invested in tool manufacture cannot also be used to complete an alternate activity. The second assumption is that each unit of time spent in manufacture decreases handling times by an equal amount. Marginal gains per time invested in tool manufacture/maintenance follow a diminishing returns curve akin to those established in patch choice models and Charnovs's (1976a, b) MVT. Finally, the authors assume that the goal of tool manufacture is to maximize net rate of energetic gain.

In an application of the model to single-occupation surface sites located in the north-central Great Basin, Bright et al. (2002) analyzed 250 radiocarbon-dated hearth features for food remnants indicative of prey choice. Contents of hearths were sorted into four categories representative of overall predicted profitabilities. Faunal remains (using numbers of identified bone specimens [NISP]) were considered high, medium, or low profitability. Floral components, such as seeds, were placed in the lowest profitability category, below even low-profitability mammals (see Herzog and Lawlor, 2016 and Chap. 13 for alternative arguments regarding the profitability of "seeds"). Categorical determinations (high, medium, and low profitability) were based on experimental data calculating the amount of time necessary to butcher and/or prepare each food type.

To evaluate the relationships between changing encounter rates and investment in technology, the authors compared the proportion of faunal and floral elements identified in associated hearths to the degree of differential investment observed in three tool types: milling stones, ceramics, and chipped stone tools. They hypothesize that (1) where seeds (and other low-profitability resources) make up only a small portion of the diet, milling stones should be made from locally available material and show no investment, such as shaping; (2) as lower-profitability resources become more common (using hearth size as a proxy), investment in milling stones and the presence of milling stones made from nonlocal materials should increase; (3) since lower-profitability resources (seeds) appear more common in the record later in time, we should see more time-intensive ceramic technology later in time co-occurring with the increasing use of these foods; (4) as the contribution of low-profitability items increases, so too should investments in ceramic types which are more expensive; and (5) a reduced emphasis on large-game hunting should be accompanied by a shift away from costly chipped stone tools. An alternate possibility not considered by the authors is that the use of technology changed the relative ranking of resources such as seeds, elevating their place in the diet.

Results were mixed, though they largely supported the authors' hypotheses. Milling stones made from exotic stone remained uncommon despite measurable increases in seed consumption. However, the number of milling stones did increase with the appearance of small-sized hearths. Specialized and expansive ceramic technologies also tracked the appearance and then increased reliance on small seeds. Likewise, as evidence for consistent large-game hunting decreased, so too did the appearance of formal, bifacial chipped stone tools. Together, these data indicate that the relationship between handling time and technological investment is linked; therefore, the model should be effective at predicting when and where technological investment and subsequent dietary shifts (see Chap. 13) may be expected. Results highlight the role of handling time as a driver in technological investment.

Bettinger et al. (2006) note several conceptual issues with the model. One such issue centers on the measurement of costs over time. The model stipulates that investment in the tool is represented by a one-to-one gain in profitabilities. However, the relationship between investment in the tool and its impact on caloric return is likely not so simple. For example, initial investment costs are often steep, while parallel improvements in profitabilities are not possible until a threshold of investment has been reached. The model assumes that all technologies are on the same gain curve and require that marginal gains are always steeper for cheap rather than costly technologies. This assumption precludes comparing different gain curves for emergent, and therefore fundamentally different, technologies. Noting these issues, and building on the premise of technological investment as a handling innovation, a subsequent set of technological investment models proposed by Bettinger et al. (2006, 2015) aimed to expand the scope of the Ugan et al. (2003) approach.

Multi-Type Technological Investment: How Long to Stay in a Given Technological Category

The Ugan et al. (2003) model is able to capture the trade-offs involved in replacing less costly versions of one category of technology with more advanced, and hence costlier, versions of the same type of technology. Building on this, an alternative set of technological investment models was proposed by Bettinger, Winterhalder, and McElreath (2006). In this paper the authors lay out two models of technological intensification derived from the MVT (Charnov 1976a, b) and Metcalfe and Barlow's (1992) field processing and transport model.

Both models assume different categories of technology have unique cost-benefit curves, and thus examine investment decisions within a category, and also shifts to new, and costlier, types of technology. Where the Ugan et al. model is limited to intensification within a technological type, the Bettinger et al. models draw attention to emergent technologies and the conditions that may lead to

dramatic changes in technological organization. They argue that costlier technologies can outperform less costly ones if profitabilities for a particular technology are maximized over the use-life of the tool (measured as cumulative time in use) in addition to the time spent in manufacture. Rather than assuming a single, continuous function as representative of all technological investment (both within and between tool types), the Bettinger et al. approach predicts investments in different tool types using separate functions for each tool category. Bettinger et al. differentiate between technological categories (a related set of forms) and classes (all known categories of artifacts used in a particular subsistence pursuit).

Here we focus on the curve-estimate model proposed by Bettinger et al. (2006). Much like the Ugan et al. model, this model builds on MVT and patch choice models. Unlike the Ugan et al. model, the curve-estimate model focuses on the amount of time that must be dedicated to handling before it becomes optimal to switch to a new strategy. Therefore, the model aims to predict the critical use time, defined as the amount of time spent in post-pursuit handling in which low-cost technologies produce the same profitabilities as high-cost technologies, as the primary variable of interest. At the critical use-time, it becomes optimal to switch from one tool category to another despite high up-front costs for development.

Variables in the model include (see Box 15.1) (1) time spent in handling (excluding time spent in tool manufacture), (2) time spent manufacturing a specific tool, and (3) the possible kcals procured as a function of the time required to manufacture. In the tradition of many other HBE models, the primary currency of the models is profitability (kcals/time). Assumptions within the curve-estimate model are that base energetic costs (kcal/h) for searching and handling (including pursuit and tool manufacture) are constant across technological categories. The model also assumes that there are no external constraints on energy or time. And, as with the Ugan et al. model, the Bettinger et al. model assumes that intensification within a tool category does not impact use-life.

An application of this model to the same data used by Ugan et al. demonstrates that by generating independent function curves, the critical times necessary for technological switching (i.e., investment in more expensive categories results in lower thresholds for switching) can be predicted. Importantly, these predictions provide a conceptual framework from which to distinguish endogenous/emergent vs. diffusion-driven technological change.

Similar to the Ugan et al. model, the Bettinger et al. models are also limited in some aspects. First, to produce multiple independent gain functions requires data on the cost of manufacture for each class of tool within a given category for each category of interest—data which is, at present, limited. Neither model considers the possibility of tool degradation or limitations on the duration of artifacts' use-life as continued investment eventually "spends" the tool. Finally, the model cannot account for transitions back to less costly and/or less efficient tool categories or types because reductions in alternate arenas are not additive assumptions. Despite these limitations, each model clearly outlines both theoretical and methodological pathways to examine technological intensification in the archaeological record.

Novel Applications of Technological Variation and Investment Models

The utility of models grounded in HBE is their simplicity and flexibility. The Ugan et al. (2003) and Bettinger et al. (2006) and Goodale et al. (2008) models provide a theoretical framework for expanded and novel investigations of technological investment. Here, we outline several novel applications and derivations borne from these basic models and from the MVT, generally.

Millingstones and Seed Intensification

Buonasera (2015), for example, adapted the Bettinger et al. point-estimate model to examine the costs and benefits of manufacturing expedient milling tools. Using experimental methods, she tested the profitabilities achieved using milling stones representing four stages of technological investment (expedient, prepared surface—minor shaping, prepared surface—moderate shaping, and metate). She then used these profitabilities to estimate the minimum use-times necessary to predict investment in minor millingstone modification. Her results demonstrated that profitabilities for seed processing (*Achnatherum hymenoides*, Indian ricegrass) did increase as level of investment increased and that the costs in manufacture (measured in units of time) were offset by the increase in profitability. Moreover, her results demonstrate that thresholds for investment in expedient milling tools (no clear evidence of exterior shaping) are rather low, indicating that investment in surface improvement should come earlier than previously assumed. Results also highlight the importance of material type in determining whether to invest in tool improvements—with some material types better suited to millingstone production than others.

Another derivation of the millingstone investment problem was taken on by Stevens and McElreath (2015). Building on both an early model of tool use-life (Ammerman and Feldman 1974) and the Bettinger et al. (2006) models, they introduce a formal technological investment model specifically designed to investigate the conditions under which multi-use tools can outperform specialized tools and vice versa. Their explicit aim was to track the decision to use one tool over another when individual tools are employed in multiple tasks. The authors use the model to explore the transition from shaped milling stones to mortar and pestle milling technology in northcentral California where archaeobotanical data suggest that by approximately 4500 BP, the acorn (*Quercus* spp.) had replaced other wild foods as a dietary staple (Wohlgemuth 1996). Coincident with increased reliance on acorn, formal pestles and mortars make an appearance in the archaeological record with their emergence and prominence in assemblages growing alongside previously existing basin-shaped millingslab implements (Basgall 1987; Glassow 1996). Stevens and McElreath (2015) tackle the problem of the transition to the mortar with a simple question, "when are two tools better than one?" Results demonstrate that decisions to invest in more expensive tools hinge not only on the ability to recoup the initial costs and the total time in use but also on the likelihood that the tool will be used repeatedly over time (see Chap. 13). No matter the improvement in efficiency, expensive technology cannot get off the ground unless there is some certainty that the item will be used repeatedly.

Flaked Stone Tools and Use-Life

Tool manufacture, like food procurement in a patch, involves a trade-off between continuing to use an increasingly ineffective tool/patch and stopping and/or leaving to create or find a better alternative. Combining raw material costs, utility (or lifespan), and production effort, Kuhn and Miller (2015) treat stone tools themselves as patches in an application of MVT to tool manufacture and use. In this model, authors consider the cost of switching between artifacts, calculating the optimal point at which to abandon one tool and invest in producing or procuring a new one. Citing reduced opportunity costs, time to manufacture is converted to energy, and energy alone is used as the currency. While the authors note that different families of artifacts may exhibit different decay curves, as in the Bettinger et al. (2006) approach, they settle on a treatment that places all flaked stone artifacts on the same utility curve following the Ugan et al. (2003) model.

The model predicts the optimum number of uses for any particular tool, and the predictions it generates are generally in line with those from the MVT itself. Increased costs raise the optimal number of uses; the more quickly the tool is spent, the earlier it is abandoned, and the optimal point

at which to abandon a tool declines as average returns increase. The authors use these predictions to examine patterns in Paleoindian spear point use-wear and retouch through time and propose two hypotheses to explain the apparent shift in discard time to later in an artifact's use-life. The first is that decreased access to source material as a function of population size drove users to hang on to existing tools for longer periods of time. Alternately, decreases in average return rates may have pushed the longer use of artifacts before discard. Here, the model provides a framework from which to begin to understand observed transitions, and hypotheses generated may be pursued further using additional lines of evidence.

Ceramics and Mobility

The advent and proliferation of pottery are widely viewed as a technological response to resource scarcity and dietary broadening. As noted above (Hawkes and O'Connell 1992), where diets are broad, investment in technology may be one of the *only* ways to achieve higher food-acquisition rates. Ceramics serve this purpose by reducing the handling costs associated with low-ranked foods such as seeds, shellfish, and bones. However, ceramics themselves are time consuming to make, difficult to transport, and susceptible to breakage.

To better understand the conditions under which groups of mobile hunter-gatherers and herders may have invested time and labor into producing pottery, Sturm et al. (2016) apply a derivation of the Ugan et al. and Bettinger et al. models to a series of hypothetical scenarios in which pottery may be adopted in contexts of high residential mobility. These test cases allow the authors to generate expectations about spatial patterns in pottery distribution, namely, that the decision to invest is complex and that expectations for use—duration of utility and anticipated cooking needs—largely constrain outcomes. Authors also note that for some forms of technological investment, social or political returns (if possible to operationalize) may be a more appropriate currency than energetic utility. Though the model has yet to be applied to existing assemblages, the authors note its utility as a heuristic for interpreting the relationships between the appearance, abundance, and distribution of pottery under variable ecological and social conditions.

Landscape Modification and Associated Technologies

Applications of the technological investment models outlined above investigate patterns in the manufacture and modification of material culture. However, in an innovative adaptation of the models, researchers Mohlenhoff and Codding (2017) use the theoretical framework of the Bettinger et al. (2006) model to examine intentional ecological niche construction. They argue that landscape modification can itself be viewed as a handling innovation, similar to the use and manufacture of any type of material tool. As such, they note that the forces/activities used to accomplish landscape modification can and do require some cost to innovate and maintain. Here, in order to invest in a given patch (i.e., modify by some technological means—fire, tillage, etc.), the marginal gains within that patch must be higher than the costs of investment. If true, the continued modification of particular patches can result in intentional niche construction—a process through which local environments are purposefully modified by inhabitants (Mohlenhoff and Codding 2017).

The authors apply the model to a series of case studies, spanning less to more costly forms of patch investment: tending acorn groves with fire, constructing fishing weirs, and adopting maize agriculture. Using both ethnographic and archaeological data to estimate the economic returns for each activity, they are able to demonstrate that investment in less costly forms of patch management/construction

such as use of fire should be ubiquitous across human societies, as is the case (Scherjon et al. 2015). However, costlier forms of niche construction such as investment in active agriculture may have only proliferated under certain environmental and socio-ecological circumstances, thus predicting the mixed expression of more intense technological investment for higher-cost forms of patch investment.

Conclusion

Critiques of the EE/HBE approach center on the perceived determinism of the models, their simplicity, violations of the underlying assumptions, and whether one should assume that there is a direct link between the observed phenotype and the adaptive demands that shaped it (a problem also known as the "phenotypic gambit") (Sterelny 2013). Applications of EE/HBE models centered on technological design and investment are not immune to these criticisms. Many include simplified assumptions and are unidirectional; most require positive gains for increased investment, however marginal, but do not and cannot account for nonoptimal investment and/or retrogression, i.e., transitions from complex to simple technology over time (as seen in Sahul and South Africa (Jones 1977; Sealy 2016)). However, the applications described here underscore that their use can and does provide a framework for interpreting patterns in the archaeological record.

Many of the phenomena described in this chapter have been investigated using alternative frameworks that explicitly address the role of culture (see Chaps 2, 3, 4, 6, and 10). Rather than revisit these methods, our goal in this chapter is to outline basic optimality models, review recent archaeological applications in light of technological decision-making and investment, and highlight both the strengths and weaknesses of the approach. To emphasize a point made by Kuhn and Miller (2015), these models do not predict that actors *will* act optimally; rather they provide a description of what that optimal behavior *ought* to look like. When the observed behavior (or in this case, material record) does not appear "optimal," as predicted by the model, this too provides an opportunity to re-evaluate and redefine model assumptions. As outlined by Sterelny (2004), this type of failure can reveal underappreciated features of local ecology or sociology, help identify unanticipated or unexpected costs, and force us to identify limits on adaptive design.

We contend that tech investment models grounded in HBE remain an underutilized tool in addressing issues of technological innovation, diffusion, and refinement. Not only can these models provide predictive power regarding the appearance of highly specialized tools, but more simply, they can be used to explain variation in archaeological assemblages generally. Because many plant and animal foods require some degree of tool-assisted processing, the models can also shed light on other dimensions of subsistence including dietary transitions and landscape modification. Filling in gaps regarding foraging behavior remains a significant area of study in archaeological research, and because physical remains of past diets are often poorly preserved and difficult to detect, technological investment models provide an additional avenue of investigation into the spatial and temporal aspects of diet breadth as well as the strategies employed by past consumers.

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