ANTHROPOLOGY

Technological complexity and combinatorial invention in small-scale societies

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Technology plays a central role in all human societies, from foraging to industrial economies. However, technological solutions come with associated costs, and in small-scale societies, technological complexity reflects this trade-off between efficiency and resource constraints. Here, we analyze this trade-off and show a sublinear scaling relationship between toolkit richness and tool part richness in ethnographic societies. This result indicates diminishing returns where each additional part contributes less to overall toolkit diversity. This scaling holds across diverse ecological and cultural contexts, suggesting a general principle of optimization in tool design. Ethnographic toolkits achieve their adaptability by reusing a core set of versatile parts and selectively incorporating more specialized parts. However, increasing richness also increases complexity, and complexity is costly. We formalize these dynamics within a combinatorial optimization framework and discuss the implications.

INTRODUCTION

All forms of life extract energy from their environments to support essential functions such as growth, maintenance, and reproduction. In human societies, this energy budget goes beyond supporting basic biological function to include meeting the combined demands of culture, infrastructure, and technology (*1*, *2*). Achieving and improving well-being involves addressing numerous interconnected challenges about how best to allocate limited resources to achieve specific goals efficiently. Throughout evolutionary history, humans have relied on technology to solve these challenges (*3*–*5*). As technology requires energy to function, in turn, it has become indispensable for harnessing and generating energy. This symbiotic relationship has deep evolutionary roots and is essential for both powering society and driving socioeconomic development.

Tools are tangible manifestations of technology, embodying the principles and knowledge that drive their creation and use. They serve as practical applications of technological advancements, enabling users to interact with and manipulate their environment more effectively. The ability to produce tools to solve problems, whether for cutting animal hides or building jet engines, is a fundamental aspect of human existence. This creative capacity has driven human development and innovation throughout history (*6*). Consequently, a long-standing research goal in many disciplines is to understand the drivers of technological variation over time and space, the patterns of invention and innovation, and the spatiotemporal variation in technological complexity (*7*–*16*). By examining these factors, researchers aim to uncover the underlying mechanisms that have shaped technologies and their impact on society. Such an understanding is crucial for informing current debates about the continued role of technological change in propelling economic growth (*16*, *17*). As researchers seek to identify the fundamental dynamics and contingencies that have influenced technological development over time and space, they often focus on how much of contemporary technological change is uniquely the result of the Industrial Revolution. Furthermore, understanding the deeper evolutionary context of technological development can shed light on the potential impact of emerging technologies, such as generative artificial intelligence (AI), on human development.

Archaeological evidence indicates that hominins have created tools for over three million years, as demonstrated by the simple stone tools found at Pliocene sites in East Africa (*18*, *19*). Before the development of farming, all humans lived as hunter-gatherers for hundreds of thousands of years, the vast majority of the evolutionary history of *Homo sapiens*. Hence, hunting and gathering served as the socioeconomic framework for the crucial development of human social organization, cooperation, and cultural evolution that continue to influence contemporary societies. Over this time, technology played a vital adaptive role as humans developed tools and techniques for hunting, gathering, and processing food, not only improving efficiency over time but also fostering innovation and problem-solving skills. These technological developments were essential for solving environmental challenges and laid the foundation for the diversity of societies seen in the historic period.

A rich understanding of the dynamics of technological complexity in human society requires examining technological complexity within the context of ethnographic small-scale human societies, characterized by a wide diversity of nonindustrial, subsistence-level populations engaged in foraging or farming. These societies provide numerous valuable cases from which we can gain insight into the fundamental dynamics of technological evolution. In addition, by studying technological complexity in small-scale societies, we get to observe how these dynamics play out in nonmarket-driven contexts, where decisions are not driven by market forces but by problem solving and fitness maximization.

This study focuses on understanding the factors that drive variation in the composition of technology among small-scale human societies (Fig. 1). We define technological complexity as the structural relationship between the number of unique tools in a toolkit, the components that compose those tools, and their ecological context—the environmental problems that technology solves.

One challenge all societies face is to find the optimal combination of tools that simultaneously minimizes the uncertainty in human-

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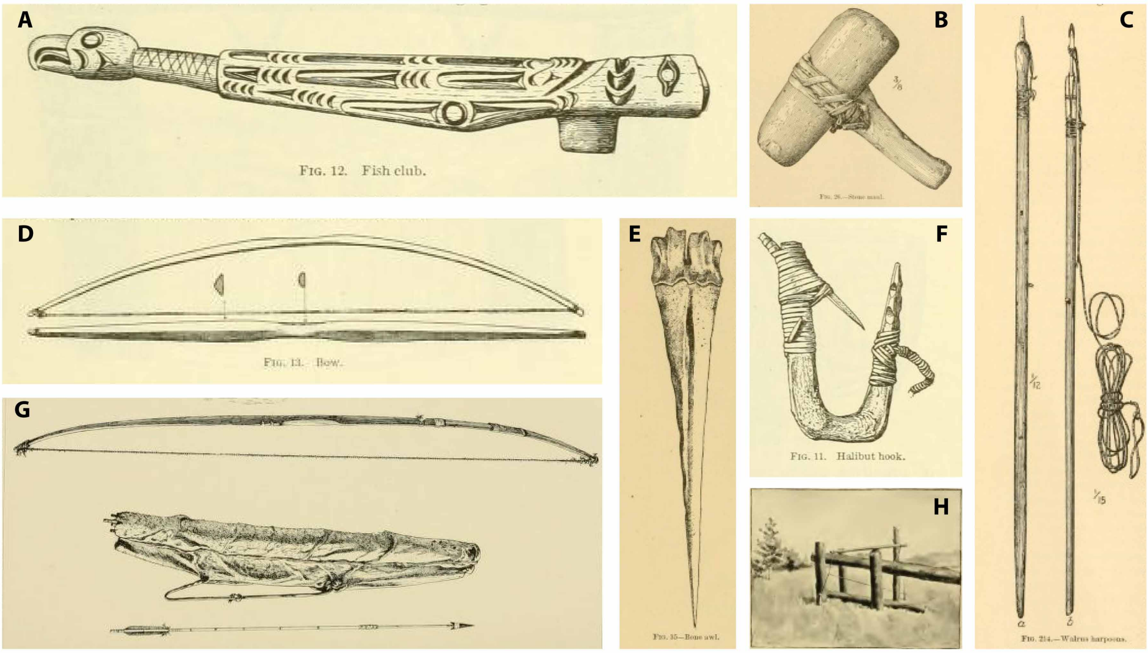

Fig. 1. Ethnohistoric examples of subsistence related tools of varying complexity. (**A**) Tsimshian fish club (*56*); (**B**) Inuit stone hammer (*57*); (**C**) Inuit walrus harpoons (*57*); (**D**) Inuit bow (*57*); (**E**) Seri bone awl (*58*); (**F**) Tsimshian fish hook (*56*); (**G**) Seri bow, quiver, and arrow (*58*); (**H**) Menominee small game trap (*59*). All images are from the Bureau of American Ethnology and are in the public domain.

environment interactions and minimizes costs. Our research focuses on how small-scale societies manage to balance the benefits of technology with the economic and material costs associated with invention, maintenance, and diversity. Specifically, we investigate the factors that drive the relationship between technological complexity and the optimization of costs and benefits in human-environment interactions. Specifically, tools cost time and energy that could otherwise be spent on other adaptively important behaviors. Our goal is twofold: to explain technological change in small-scale societies and to gain fundamental insights into how technologies are constructed in these societies. By doing so, we aim to establish a formal framework and an empirically robust baseline for understanding the evolutionary context from which human technological complexity emerged and increased.

The nature of technological complexity

Anthropologists and archaeologists have documented remarkable variation in the technological complexity—the composition of toolkits in a society—of small-scale societies across space and time, and the causes of this diversity are the source of much debate (*20*–*34*). There are many ways "technological complexity" could be measured in a dataset. In this study, our measure is the relationship between the number of unique tools in a toolkit and the number of unique parts that are used in the manufacture of those tools. We define this more formally below.

We focus on subsistence tools, the technology used to facilitate extracting food resources from the environment, such as spears, nets, fishing weirs, harpoons, small game traps, digging sticks, and so on. All environments are to some degree both dynamic and stochastic, varying in both productivity and predictability over time and space. Hence, all human-environment interactions involve uncertainty (*35*). Humans seek to minimize this uncertainty by building behavioral models from which to make predictions about the likely outcome of their implementation. Tools are the material interface of these strategies; the physical structures engineered from matter to facilitate interactions with the world. Technological solutions to problems of environmental uncertainty might include knowing how to excavate a tuber using a digging stick, killing an antelope with a dart, or trapping a fish in a stream with a weir. Thus, tools are adaptive inventions in material form that seek to solve the immediate problem of extracting resources, thus playing a central role in solving the broader meta-problem of maximizing fitness.

The benefits of technology, however, come with unavoidable costs. Fundamentally, a society must balance the benefits of reducing environmental uncertainty with the costs of toolkit design, manufacture, and maintenance. In subsistence societies, with limited access to resources, this optimization is particularly crucial as technology costs time and energy resulting in opportunity loss, and risk of failure is measured in the survival rates of offspring. This is because time and energy devoted to manufacturing and maintaining technology is time that could be devoted to other fitness-promoting tasks, such as childcare, foraging, or reproduction. Raw materials must be gathered, solutions designed and engineered, tools maintained, and the knowledge to manage all aspects of the technological repertoire needs to be learned by individuals and transmitted faithfully across generations. As a consequence, the increase in the diversity and complexity of toolkits is constrained by the increased costs inherent in such an increase.

Here, we develop an optimization model of technological complexity and the role it plays in reducing uncertainty in human-environment interactions. This model formalizes the benefits of reducing uncertainty in the environment with the costs of tool use. We then parameterize this model using ethnographic data on the composition of toolkits used by small-scale hunter-gatherer and food-producing societies across the planet. We show that toolkit richness (the number of unique tools in a toolkit) scales sublinearly with component richness (the number of unique part types). This relationship holds regardless of the broad subsistence strategy (immediate-return system hunter-gatherer, delayed-return system hunter-gatherer, or farmer). We argue that the complexity of subsistence technology in small-scale societies follows this relationship as a response to the benefits of reducing uncertainty in a given environment and the costs associated with innovating new technology and maintaining that technology.

The model

To develop the context in which toolkits occur and the problems they solve, we build a minimal model of the environment, its stochasticity, and the adaptive role technology plays in all human lifestyles, conditioned on its costs. These costs include the costs of acquiring raw materials, engineering new components, and maintaining tools over their use-life. Here, the objective is to find the optimal toolkit that maximizes its utility while minimizing its costs. We treat the optimization involved as an instance of combinatorial optimization, that is, finding the optimal subset or arrangement of discrete elements from a finite set, where the objective is to minimize (or maximize) a function subject to constraints (*36*).

Environmental uncertainty as a constraint space

The biophysical environments in which human societies are embedded—and from which humans seek to extract energy efficiently in the form of plant and animal food resources—are inherently stochastic. Because food resource availability fluctuates through time and space, there is inherent uncertainty in all subsistence related human-environment interactions. There is uncertainty at all environmental scales, from the location of individual prey animals to the seasonality of environments and so some of these scales of uncertainty are more amenable to reduction through technological intervention than others. We begin by modeling the environment as a constraint space $\mathbf{C}$, composed of multiple dimensions each representing different sources of variability

$$\mathbf{C} = \left[V_{\mathrm{R}}, V_{\mathrm{E}}, P, K, \ldots\right] \tag{1}$$

where V_{R} is the variability in resource availability, V_{E} is the environmental variability (e.g., seasonal changes and climatic events), K is the predation or other external risks, and E is the energy expenditure required for resource acquisition or survival. Each dimension of $\mathbf{C}$ quantifies a specific type of uncertainty affecting survival and reproduction.

To capture the overall uncertainty in the environment, we define $P(\mathbf{C})$ as the joint probability distribution $P(\mathbf{C}) = P\left(V_{\mathrm{R}}, V_{\mathrm{E}}, K, E, \ldots\right)$. Defining X as the set of all possible outcomes in the constraint space, $X = \{x_1, x_2, \ldots, x_n\}$, each $x \in X$ represents a specific configuration of $V_{\mathrm{R}}, V_{\mathrm{E}}, K, E, \ldots$, with an associated probability $P(x)$, which quantifies the likelihood of observing x_i, given the probabilistic structure of the constraint space.

Each dimension of the constraint space $\mathbf{C}$ has an associated uncertainty, defined as an entropy $H(x)$, and so $H(\mathbf{C}) = H\left(V_{\mathrm{R}}\right) + H\left(V_{\mathrm{E}}\right) + H(K) + H(E) + \ldots$, which quantifies the unpredictability over all outcomes (i.e., an instance of a human-environment interaction)

$$H(\mathbf{C}) = -\sum_{x \in X} P(x) \log P(x) \tag{2}$$

where $P(x)$ is the probability of an outcome x, given the constraints in $\mathbf{C}$, and X is the set of all possible outcomes. The entropy $H(\mathbf{C})$ quantifies the unpredictability in human-environment interactions, and higher entropy indicates greater uncertainty in these outcomes. The use of the entropy formalism to characterize uncertainty is a widely accepted approach in many scientific fields, and its use here highlights that uncertainty reduction necessitates increased information, i.e., knowledge about the environment.

The toolkit and its components

The use of tools effectively reduces the uncertainty in the environment by providing reliable and efficient means to manipulate the environment. Tools enable users to perform tasks with greater precision and control, such as hunting, gathering, and food processing. This directly affects their ability to predict and manage environmental challenges. By enhancing the efficiency and effectiveness of these activities, tools help to stabilize resource acquisition and minimize the risks associated with environmental variability.

A toolkit is a collection of tool types $T = \{t_1, t_2, \ldots, t_n\}$, each designed to reduce uncertainty in specific dimensions of $\mathbf{C}$. Each tool type $t_i \in T$ is a function that maps constraints to a real value representing its performance in reducing uncertainty

$$t_i\colon \mathbf{C} \to \mathbb{R} \tag{3}$$

We then define toolkit richness T_n as the cardinality of the set T.

Individual tool types are constructed from the set of unique component parts $P = \{p_1, p_2, \ldots, p_n\}$ Fig. 2. We define component part richness P_n as the cardinality of the set P. Each part $p_i \in P$ contributes to the construction of tools and, indirectly, to uncertainty reduction. This means that a single tool type t_i is composed of a subset of all available parts, so $t_i \subseteq P$, and so $\forall t_i \in T, t_i \subseteq P$. Therefore, $T = \{t_i \mid t_i \subseteq P, \ i = 1, 2, \ldots, T\}$; that is to say that the toolkit T is composed of a suite of unique tool types, t_i, each of which is composed of unique component parts, p_i, which, when combined, form the component part richness P.

In our dataset, a unique part, p_i, is defined as "an integrated, physically distinct, and unique structural configuration that contributes to the form of a finished artifact" (*29*). For example, a digging stick is composed of one unique part; a digging stick with a cylindrical weight is two parts; a walrus harpoon or a snare might be composed of dozens of parts. A unique tool type, t_i, is "an extrasomatic form that is removed from a natural context or manufactured

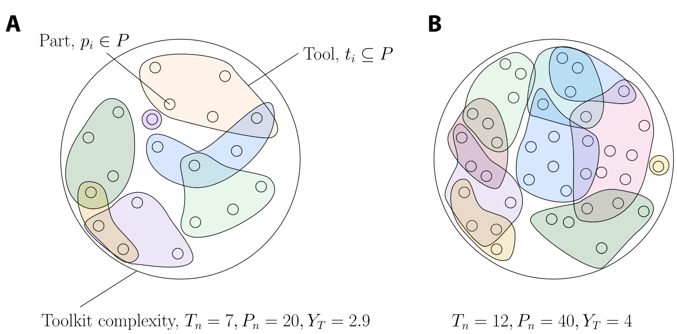

Fig. 2. Tool parts, types, and complexity. Panel (**A**) represents a toolkit comprised of seven individual tool types constructed from 20 unique parts with an average tool complexity of 2.9 parts per tool. Panel (**B**) represents a toolkit of 10 individual tool types constructed from 40 unique parts with an average tool complexity of four parts per tool. $P_n T_n$, Y_T.

and is applied directly to obtain food" (*29*). A stone used for throwing is a unique tool, as are arrows, bows, snares, traps, and harpoons. In farming societies, subsistence-related tools might include lassos, tethers, hoes, and sickles.

Tool construction

The upper bound of toolkit richness is set by the theoretical maximum number of tools, $T_{\max}$, that could be generated from the combinatorial possibilities of all subsets of all parts. If all possible subsets of all P_n unique parts resulted in a viable tool, then the total number of possible combinations is

$$T_{\max} = 2^{P_n} \quad (4)$$

where each part can either be included or excluded from a tool, leading to 2^{P_n} subsets. This exponential growth reflects the combinatorial explosion of potential tool types as more parts become available. However, in practice, such exponential richness is never realized because of the variety of constraints discussed below. Although $T_{\max}$ can grow exponentially, real-world toolkit richness is constrained by multiple factors: The actual number of functional tools produced by any combination of parts is a tiny fraction of the theoretical maximum.

While some tools are composed of a single component—such as a digging stick—composite tools are constructed from a subset of parts. Tools in small-scale societies typically involve no more than a few components (m-sized subsets). For example, no single tool type will include all available component parts and so $m \ll P_n$. The number of such subsets is given by the binomial coefficient

$$T_{\text{restricted}} = \binom{P_n}{m} = \frac{P_n\,!}{m\,!\,(P_n - m)\,!} \quad (5)$$

which for large P_n and small m simplifies to

$$T_{\text{restricted}} \sim \frac{P_n^m}{m\,!} \quad (6)$$

This polynomial growth is much slower than the exponential growth of $T_{\max}$, significantly reducing the actual number of tools.

However, even for limited subsets, the actual production of realized tools from component parts is further restricted by many other factors. The material properties of the parts constrain the combinatorial possibilities, as there are only so many ways in which wood, bone, stone, metal, and other components can be combined to produce a functional tool. It is also likely that the cultural norms of a society restrict the particular forms of certain tool types. For example, there are many ways to construct a functional bow, but a given society will have particular traditions that limit the types of bow they manufacture (*37–39*). In addition, the ability to manufacture components will also be limited by the abundance and spatial availability of materials in the environment, and most combinations of even a small number of parts will not produce a functional tool. Moreover, societies may prioritize certain tools over others based not only on their utility but also on symbolic importance or other cultural beliefs and practices.

Incorporating these constraints, we express the relationship between toolkit richness T_n and part richness P_n in the general form

$$T_n \propto P_n^{\beta} \quad (7)$$

where $\beta = d\ln T_n / d\ln P_n$ represents the elasticity of toolkit richness T_n with respect to part richness P_n. Equation 7 captures a range of multiplicative responses, with the value of β determining whether the relationship between part and types is superlinear ($\beta > 1$) or sublinear ($\beta < 1$).

Toolkit effectiveness

The contribution of a tool type t_i to reducing uncertainty is then modeled by a reduction function $r_i(\mathbf{C})$

$$r_i(\mathbf{C}) = H(\mathbf{C}) - H_{t_i}(\mathbf{C}) \quad (8)$$

with $H_{t_i}(\mathbf{C})$ denoting the entropy after applying the tool type t_i. Here, the effectiveness of a tool type is explicitly the reduction in entropy of the outcome. We consider the simplest case where the overall effectiveness of a toolkit T in reducing uncertainty is given by

$$R_T(\mathbf{C}) = \sum_{i=1}^{n} w_i r_i(\mathbf{C}) \quad (9)$$

where $r_i(\mathbf{C})$ is the uncertainty reduction contributed by tool type t_i, and w_i is a weight representing the importance or relevance of t_i in the given environmental context. That is to say, in Eq. 9, the overall effectiveness of a toolkit is simply the weighted sum of the effectiveness of its individual components.

Each tool type t_i may target specific dimensions of $\mathbf{C}$. For example, a fishing net reduces variability in resource availability (V_R), a spear reduces predation risk (K), and a storage vessel reduces variability in environmental availability (V_E). Thus, a toolkit's effectiveness $R_T(\mathbf{C})$ reflects the combined impact of tools across all relevant dimensions. Note that Eq. 9 could be extended to consider more complicated situations where synergistic interactive effects on uncertainty reductions may arise between tool types. For example, the combined use of fishing weirs and fishing spears may allow the harvesting of entirely new sources of aquatic resources on rivers, or the combined use of hunting nets and digging tools might provide access to new types of terrestrial prey such as fossorial mammals.

Invention and maintenance costs

We assume that the costs of inventing and maintaining a new tool type are related to the number of constituent parts that make up the form, an assumption justified by several considerations. More parts generally mean more complexity, which requires additional time and effort to design, assemble, and maintain the tool. Each part needs to be sourced, manufactured, and integrated into the final product. Each component of a tool type requires specific materials and resources. The more parts there are, the greater the variety and quantity of resources needed, which can increase costs. Tools with more parts are likely to require more frequent maintenance and repairs. Each part can wear out or break, necessitating replacements or repairs, which adds to the overall cost. Creating and maintaining complex tools often require specialized skills and knowledge. Learning the skills to handle these tasks can be costly and time-consuming.

By assuming that the costs of inventing and maintaining a tool type in the toolkit are proportional to its number of unique parts, $C \propto P$, a significant constraint is introduced on how societies balance the benefits of increasing toolkit richness, T_n, with the economic, cognitive, and material costs of increasing part richness, P_n. This refinement to the relationship $T_n \propto P_n^{\beta}$ highlights a trade-off between technological richness and resource use. If the cost of initially inventing and then maintaining a tool type is simply proportional to the number of unique parts, the total cost of a toolkit can be expressed as

$$C = \lambda P_n \quad (10)$$

where λ is a proportionality constant representing the per-unit cost of innovating, maintaining, or integrating a new part.

The net utility U of increasing part richness can be specified as the difference between the benefits derived from toolkit richness and the associated costs

$$U = T_n - C \tag{11}$$

Substituting the scaling relationship for T_n

$$U \propto P_n^{\beta} - \lambda P_n \tag{12}$$

and so the utility is clearly dependent on the values of β and λ.

Optimal part richness

The utility to be optimized is the balance between the adaptive benefits of tools in reducing environmental uncertainty and the costs associated with inventing, maintaining, and diversifying those tools. To maximize utility, societies must balance these competing effects by selecting an optimal P^*, the part richness that maximizes U. The optimal P^* can be found by differentiating U with respect to P and setting the derivative to zero

$$\frac{dU}{dP_n} = \frac{d}{dP_n}\left(P_n^{\beta} - \lambda P_n\right) = 0 \tag{13}$$

Differentiating and solving for optimal part richness P^* yields

$$P^* \propto \left(\frac{\beta}{\lambda}\right)^{\frac{1}{1-\beta}} \tag{14}$$

Equation 14 shows that the optimal part richness decreases as the cost of invention, λ, increases, reflecting a trade-off where higher costs limit technological diversity.

The ultimate goal of a toolkit is to minimize overall environmental uncertainty while accounting for costs and constraints. Combining the results derived above, we find that the optimal toolkit T_n^* is defined as the objective function

$$T_n^* = \underset{T}{\operatorname{argmin}}\left[H_T(\mathbf{C}) + \lambda C_T\right] \tag{15}$$

where $H_T(\mathbf{C})$ is the residual uncertainty after applying the toolkit T_n, C_T is the total cost of the toolkit, including material, cognitive, and maintenance costs, and λ is a weighting factor balancing uncertainty reduction and invention cost. A higher λ places greater emphasis on minimizing costs, while a lower λ allows for more focus on reducing uncertainty. The optimal toolkit T^* minimizes the combined burden of residual uncertainty in human-environment interactions and the cost of toolkit production, with the weighting parameter λ determining the relative importance of cost versus uncertainty reduction.

Toolkit complexity and diversity

If the toolkit richness of a society is the result of cultural technological norms transmitted over generations, modified by decisions made by individuals within the society as they fine-tune their adaptive strategies to local environmental conditions over some window of time, we can assume $T_n \approx T_n^*$, and so the observed toolkit richness is near some local optimum. Toolkit richness $T_n(P)$ describes the number of tools in the toolkit as a function of the number of unique parts P_n. The richness reflects the potential complexity and adaptability of the toolkit

$$T_n(P) = c_1 P_n^{\beta} \tag{16}$$

where $\beta = d\ln T_n(P) / d\ln P_n$ is the exponent, and c_1 is a proportionality constant reflecting technological, cultural, and ecological constraints. Rearranging Eqs. 10 and 16, we have an expression for the cost of richness

$$C\left(T_n\right) = \lambda P_n = c_2 T_n^{1/\beta} \tag{17}$$

Defining average tool complexity Y_T as the ratio of parts P_n to toolkit richness T_n, or the average number of parts per tool, P_n / T_n, we find

$$Y\left(T_n\right) \propto T_n^{1-\beta} \tag{18}$$

Therefore, toolkit richness, complexity, costs, and their optimal dynamics are largely dependent on the value of the parameter β. Having established the model, we now turn to estimating β from data.

RESULTS

We studied technological complexity across three broad categories of small-scale subsistence level societies (see Fig. 3): (i) Immediate-return hunter-gatherers are societies that consume food and other resources soon after acquisition rather than storing them for long-term use. They typically rely on daily foraging of wild plants and animals, emphasizing mobility, egalitarianism, and sharing within the group.

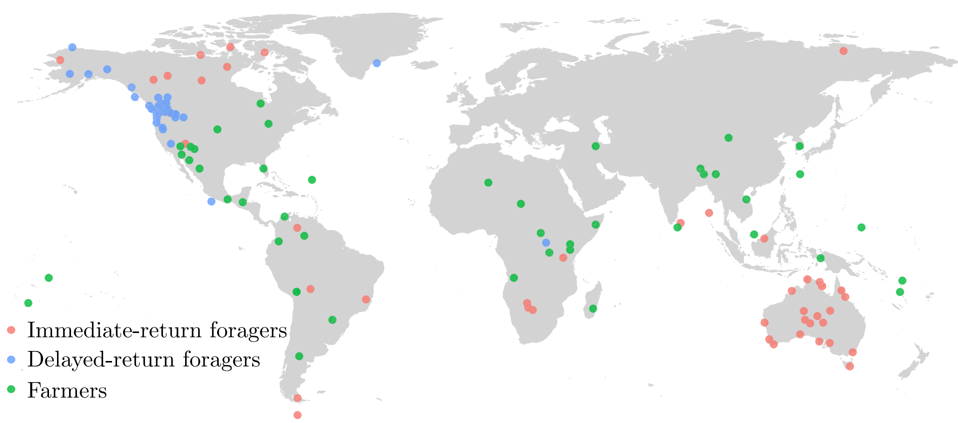

Fig. 3. The global distribution of the 127 societies in the dataset. Spatial coverage is clustered and uneven, as is typical for anthropological datasets. We control for these effects statistically.

Social organization tends to be flexible, with minimal hierarchy, as there is little accumulation of surplus to create wealth disparities. (ii) Delayed-return hunter-gatherers are societies that invest effort into acquiring, processing, and storing resources for future use, rather than consuming them immediately. They may engage in activities such as food preservation and territorial management and often construct durable hunting and fishing equipment. These societies often exhibit more complex social structures, including inherited leadership roles and ownership rights over stored resources, leading to greater social inequality to immediate-return hunter-gatherers. (iii) The farmers we refer to here are traditional small-scale subsistence farming communities that primarily grow food for their own consumption rather than for large-scale trade or market exchange. They rely on low-intensity agricultural techniques, such as shifting cultivation, swidden (slash-and-burn) farming, or small permanent plots, often supplemented by hunting, fishing, or gathering.

Figure 4 shows that immediate-return system hunter-gatherers consistently have the lowest values of toolkit richness, tool part richness, and average tool complexity. Farmers have rich and diverse toolkits, but the most complex technologies are found in delayed-return system hunter-gatherers. This is because most of our sample of delayed-return system hunter-gatherers are from the Northwest Coast of North America where subsistence economies are particularly diverse and seasonal.

However, our results are statistically independent of these three lifestyle groupings. Figure 4 shows that toolkit richness is a sublinear function of component part richness as

$$T_n(P_n) = c_0 P_n^{0.7} \tag{19}$$

The results reported in Table 1 show that the fixed effect of lifestyle grouping is not significant, both in terms of the intercept and the slope: The result summarized in Eq. 19 is common to small-scale societies, independent of whether groups are immediate-return system hunter-gatherers, delayed-return system hunter-gatherers, or farmers, even after accounting for spatial autocorrelation.

The sublinearity of Eq. 19 indicates the diminishing returns of technological richness to component part richness: Groups that have double the number of tool parts have subsistence toolkits that are on average only about 62% richer in terms of tools. This implies that functional tools are increasingly difficult to engineer from more parts, and while some groups have richer toolkits than others, this richness comes at an increasing cost and is increasingly rare. We return to this in Discussion.

We can also summarize these results in terms of average tool complexity, Y_T. Given $\beta = 0.7$, average tool complexity increases with toolkit richness as

$$Y_T = c_1 T_n^{0.3} \tag{20}$$

Doubling toolkit richness leads to tools that are, on average, 23% more complex. Or, alternatively, societies that diversify their technologies do so by recombining their component parts to generate more complex tools. Hence, diversity is not free; it comes at a steep cost.

A technology that seems locally optimal in one society may not be locally optimal in another and that difference comes at a cost. All adaptive solutions come at the price of time, energy, and opportunity costs, and so different adaptive strategies have different pay-offs. It is in this sense that there is no free lunch for technological diversity: Ostensibly, societies do not get to diversify their technologies for free.

DISCUSSION

The results we present here show that the technologies of small-scale societies are shaped by a dynamic interplay of invention, resource limitations, and problem solving. This relationship is captured by the diminishing returns of toolkit richness T_n, the number of distinct tools, with tool part richness P_n, the number of unique components available for construction. We show across a global sample of 127 small-scale societies a relationship of $T_n \propto P_n^{0.7}$, indicating a sublinear growth regime that reflects the constraints inherent to technological systems (Fig. 5).

Our model indicates that there is a considerable amount of information encoded in the functional form of this relationship and in the value of the parameter β. The fact that we observe sublinearity (i.e., $\beta < 1$) indicates that as the number of unique tool parts increases, the growth of toolkit richness slows. In other words, adding an additional tool type to the toolkit requires an even greater number of components. This pattern implies that the practicalities of designing, engineering, and maintaining tools are shaped by factors such as material properties, material availability, design constraints, and opportunity costs, all of which place mounting constraints on the practical richness of toolkits. Although the theoretical potential for the combinations of parts is vast, only a small subset of those combinations is practically viable, resulting in the observed sublinear scaling.

Because technology is the material solution to reducing environmental uncertainty or solving problems more generally, if there

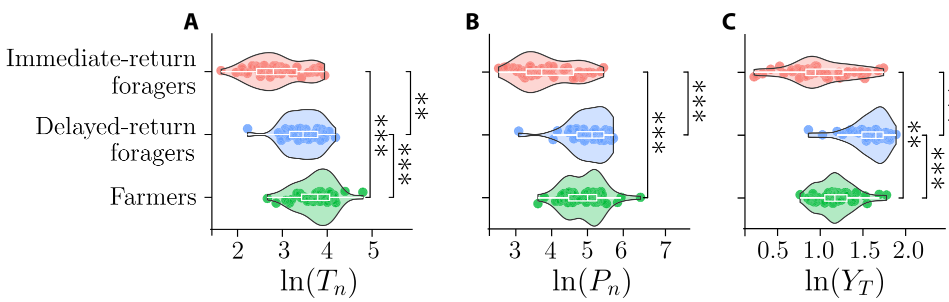

Fig. 4. Descriptive statistics of toolkit types, parts, and complexity. Violin plots of (**A**) toolkit types T_n, (**B**) parts P_n, and (**C**) average tool complexity Y_T. Farmers have the highest toolkit richness (A), whereas delayed-return system hunter-gatherers have the most complex technologies (C). Vertical bars represent statistically significant pairwise Wilcoxon tests at the 95% confidence level where $^{***}P < 0.001$ and $^{**}P < 0.01$.

Table 1. Results of the spatially explicit mixed model scaling of toolkit complexity in small-scale societies. Imm. Ret., immediate-return; Del. Ret., delayed-return. Cond.s.e., conditional standard error.

Fixed effects	Dependent variable		
	$\ln T_n$	Cond.s.e.	*t* value
$\ln P_i$	0.71	0.03779	18.85884
$G_{\text{Imm.Ret.forager}}$	0.004278	0.16434	0.02603
$G_{\text{Del.Ret.forager}}$	−0.354535	0.26915	−1.31724
G_{Farmer}	−0.043120	0.24807	−0.17382
$\ln P_i{:}G_{\text{Del.Ret.forager}}$	0.054362	0.06063	0.89663
$\ln P_i{:}G_{\text{Farmer}}$	0.058240	0.06344	0.91808
Random effects			
ν	0.1543916		
ρ	0.0163354		
λ	0.04262		
Residual variance			
ϕ	0.00468066		
Likelihood values			
Log$L$	44.73024		
Re.log$L$	32.20775		
Observations	127		
Pseudo R_2	0.92		

were no costs associated with richness, toolkits should be designed to be rich enough to address all environmental uncertainties. In such a scenario, for any environmental problem, there would be a corresponding technological solution. However, in reality, traditional technologies face numerous constraints that limit the effectiveness of a toolkit. These constraints include the availability of resources, the complexity of the environment, and the economic and material costs of creating and maintaining rich toolkits. Our model details these trade-offs and demonstrates empirically how they manifest across different societies. Specifically, we show how small-scale societies balance the adaptive advantages of technology with the economic and material costs of invention, maintenance, and diversity. By examining these trade-offs, we aim to gain fundamental insights into the construction of technologies in small-scale societies and establish a principled framework for understanding the evolutionary context from which human technological complexity emerged.

The diminishing returns indicated by the sublinear scaling suggest that small-scale societies prioritize functionality, efficiency, and robustness in the design of their subsistence toolkits. While a handful of versatile parts might form the basis of the majority of tools across this sample of small-scale societies, additional parts tend to be either highly specialized or redundant. Such specialization likely emerges in response to complex ecological niches, where new tools are required to solve specific problems, such as intercepting, harvesting, and processing locally specific food resources. Despite the need for specialization, most technological systems in small-scale societies appear to be optimized for efficiency, flexibility, and adaptability by relying on a core set of reusable parts.

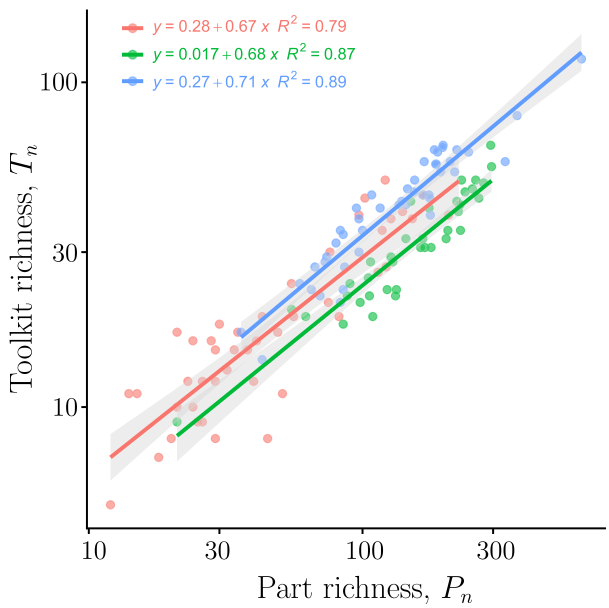

Fig. 5. The scaling relationship of toolkit richness and part richness. Toolkit richness T_n as a function of part richness P_n across the three lifestyle types, immediate-return systems hunter-gatherers (red), delayed-return system hunter-gatherers (blue), and farmers (green). Slopes range between 0.67 and 0.71. Fitted straight lines are ordinary least squares regression models but see Table 1 for full results from the mixed effects model. These data show the remarkably tight sublinear relationship between toolkit richness and tool part richness, indicating diminishing returns. R^2, coefficient of determination.

Our model develops the perspective that toolkits are material components of behavioral strategies that help societies reduce environmental unpredictability in their interactions with the environment. Each tool type contributes to reducing some dimension of uncertainty, and the collective effectiveness of the toolkit is a result of the integrated contributions of its individual components. The diminishing returns of adding more tools, as evidenced by the observed scaling, suggest that while toolkits are designed to address the most significant environmental challenges, they also incorporate overlapping functionalities to ensure robustness in the face of stochastic environments.

The generality of the observed scaling relationship across different socioeconomic lifestyles suggests that the principles governing technological diversity are deeply embedded in the constraints of human cognition, material availability, and social organization. The consistency of the scaling exponent across different types of small-scale societies—such as hunter-gatherers and small-scale food producers—further underscores that toolkit construction is primarily driven by universal principles of cost-efficiency rather than cultural idiosyncrasies.

However, technological invention and innovation (that is, adoption) are costly, and small-scale societies must weigh these costs against the potential benefits of increasing toolkit richness. The inclusion of costs ($C \propto P$) in the model helps explain why societies cannot expand part richness indefinitely. Instead, the optimal part richness (P^*) is determined by the trade-off between the diminishing returns of adding new tools and the costs associated with invention. High invention costs lead societies to maximize the utility of each part, which is reflected in the sublinear relationship, where most of the toolkit richness comes from reusing a small number of versatile parts. The implication here is that the optimal part richness changes with the costs. If societies suddenly gain access to new ideas and new raw materials, the optimal tool part richness will likely change. Similarly, this model suggests that as tool part manufacturing becomes more standardized, costs are reduced, and so increased technological complexity can be driven not just by the need to solve more problems (i.e., necessity being the mother of invention) but by the reduced cost of doing so.

Understanding the drivers of technological variation of traditional small-scale societies across the world is an important focus of anthropological and archaeological research (*29*, *40*). The causes underlying the creation of toolkit variation have been the subject of intensive research through the development of models (*26*, *41*–*47*) and the analysis of toolkit structure in relation to possible causal drivers (*20*–*34*, *40*). This latter set of studies focuses on identifying drivers of toolkit richness and complexity through correlational observations. From these analyses, two main primary drivers have emerged. One is environmental risk (*20*–*25*); the other is population size and connectedness (*22*, *26*, *27*, *45*). Here, we have taken a different approach. Rather than trying to identify the primary drivers of complexity, our study has investigated the generating mechanisms, the ultimate function of technology, and the optimization that results. The foundational assumption of the model presented here is that the combination and recombination of existing tools is a principal generator of technological novelty. Our model shows that there are features of toolkit structure—features not recognized in previous studies—that constrain the combinatorial process.

Our study has broader implications for understanding the evolution of technological complexity in both prehistoric and modern contexts. The relationships governing toolkit richness and part richness highlight the inherent constraints of technological invention. These constraints are as relevant to the subsistence tools of small-scale societies as they are to the complex technologies in industrialized economies. While technological invention and innovation are never free, the social and biophysical contexts in which human creativity can be expressed—along with their incentives—have greatly changed over time.

In nonindustrial societies, the invention of new tools is often driven by immediate practical needs and limited by the availability and properties of local materials. Inventions were typically incremental, building on existing technologies within small, dispersed social groups. Moreover, invention is relatively rare as technological traditions emphasize reliability, predictability, and resilience over generations, with a strong reliance on inherited traditional knowledge and cultural transmission (*48*–*50*). In contrast, the rate of invention, novelty, and creativity in industrialized societies benefits from advanced scientific knowledge, global communication networks, markets, and sophisticated manufacturing technologies (*6*). If combinatorial search in a space of technological opportunities is a common source of technological novelty across time, then what accounts for the combinatorial explosion that characterizes modern economic development? It seems likely that the main difference between inventing new tools in nonindustrial and industrial societies lies in the scale, complexity, and resources available for invention, particularly the energy available for expanding technological complexity.

The efficiency and adaptability observed in small-scale toolkits provide valuable insights into the dynamics of technological diversity, invention costs, and the optimization strategies used by societies to balance functionality, complexity, and resource use. By examining these dynamics, we can better understand how societies have historically managed the trade-offs between technological innovation and resource constraints. This understanding is crucial for contemporary technological development, as it highlights the importance of optimizing toolkits to meet human needs while managing costs and resource limitations.

Whether humanity can continue to benefit from the "combinatorial explosion of knowledge" as a principal driver of socioeconomic development depends on how effectively these constraints are managed and relaxed. This can be achieved through the development of new technologies and innovative social arrangements that enhance the efficiency and sustainability of technological advancements. Current concerns about the voracious consumption of electricity by data centers and generative AI (which operates by searching for solutions in a vast combinatorial space of words, phrases, and contexts) serve as a reminder of the energy requirements of invention.

MATERIALS AND METHODS

Materials

We compiled data on toolkits from previously published studies that examined the technology used by 127 small-scale societies in terms of the number of distinct tools and tool parts in their subsistence toolkits (*22*, *23*, *29*, *51*–*53*). Our coverage is global but uneven, which we control for statistically (see Fig. 3). Two of the studies recorded toolkit data from 35 hunter-gatherer groups (*23*) and 45 small-scale food-producing groups (*22*, *24*), including populations from Africa, Asia, the Americas, and Oceania. One of the studies includes 21 populations from the Northwest Coast region of North America (*51*), and the other regional includes 17 Australian Aboriginal groups (*53*). In the few cases of overlap in these datasets when the same group was recorded in different studies, we used the data from the most recent source. All data needed to evaluate the conclusions in the paper are available at (*54*).

We chose these four datasets specifically as they are consistent in their use of Oswalt's method of counting tools and tool parts (*29*, *40*). Oswalt devised two measures of toolkit structure, the number of "subsistants" and "technounits," to make replicable, quantitative comparisons of toolkits used by different groups. We refer to subsistants in this study simply as tools. Examples of subsistants or tools include wooden club, spear, bow, fish lure, pitfall, and snare (*20*, *40*). Oswalt defined a technounit as an "integrated, physically distinct, and unique structural configuration that contributes to the form of a finished artifact" (*29*); in other words, technounits are the unique parts of a tool. For example, a single tool, such as a spear can be made of three parts—a shaft, a barbed point, and a binder—or if the spear also has an attachment line and float it will have five parts.

Statistical methods

To measure the relationships between tool types and tool parts across groups of differing subsistence economies and geographies, we use a spatially explicit mixed effects model, implemented in R using the spaMM package (*55*). These models control for spatial autoregression by modeling spatial effects as a random variable. We also introduce three broad classes of socioeconomic lifestyle as a fixed effect; immediate-return system hunter-gatherer, delayed-return system hunter-gatherers, and farmers. These fixed effects were allowed to interact with technological complexity. This is necessary as these categories of lifestyles encompass a broad range variation in subsistence economy, landscape mobility, sociopolitical organization, settlement patterns, and so on. Hence, it may be the case that technological complexity manifests differently across these categories. The model has the following analytical form

$$\ln T_{n,i} = \left(\beta_1 \cdot \ln P_{n,i}\right) + \left(\beta_2 \cdot \ln G_i\right) + \left(\beta_3 \cdot \ln P_{n,i} \cdot \ln G_i\right) + Z_i + \epsilon_i \quad (21)$$

where $\ln T_{n,i}$ is the toolkit richness, the response variable for observation i; $\ln P_{n,i}$ is the component part richness, and $\ln G_i$ is the fixed effect of lifestyle type; these are the predictor variables for observation i; β_1, β_2, and β_3 are fixed effect coefficients associated with the predictors and their interaction; Z_i is a random effect representing the spatial correlation modeled using the Matérn covariance function, incorporating spatial coordinates of longitude and latitude; and ϵ_i is the residual error term for observation i.

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