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Modelling the emergence of open-ended technological evolution

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Humans stand alone in terms of their potential to collectively and cumulatively improve technologies in an open-ended manner. This open-endedness provides societies with the ability to continually expand their resources and to increase their capacity to store, transmit and process information at a collective-level. Here, we propose that the production of resources arises from the interaction between technological systems (a society's repertoire of interdependent skills, techniques and artifacts) and search spaces (the aggregate collection of needs, problems and goals within a society). Starting from this premise we develop a macro-level model wherein both technological systems and search spaces are subject to cultural evolutionary dynamics. By manipulating the extent to which these dynamics are characterised by stochastic or selection-like processes, we demonstrate that open-ended growth is extremely rare, historically contingent and only possible when technological systems and search spaces co-evolve. Here, stochastic factors must be strong enough to continually perturb the dynamics into a far-from-equilibrium state, whereas selection-like factors help maintain effectiveness and ensure the sustained production of resources. Only when this co-evolutionary dynamic maintains effective technological systems, supports the ongoing expansion of the search space and leads to an increased provision of resources do we observe open-ended technological evolution.

1. Introduction

Over the last 300,000 years, our species has improved, diversified, and complexified the range of technologies available to us, allowing human societies to collectively address various needs and goals as well as tackle diverse challenges and problems [1–4]. Even in their simplest guises, human technologies constitute complex cultural systems of interdependent skills, techniques, artifacts and knowledge [5–8] that are collectively shared, culturally transmitted and cumulatively evolving [3,9–15]. Technological systems are powerful in this respect because humans are able to collectively adapt [16,17] and discover highly optimized cultural solutions for a wide variety of social, cultural and ecological niches [18]. What makes technology special, however, is that it falls under a special class of dynamics exhibiting *open-ended evolution* [19–30]: a process where technological systems continually produce and maintain increasingly diverse and complex technological traditions that solve an ever-expanding space of needs, problems and goals [2,31–34]. It is this open-ended capacity that ultimately underpins our ability to extract and harness diverse sources of energy, to access and manufacture novel materials, and to transmit and process information at vast scales [22,33,35,36].

Explaining why and how human technology is uniquely open-ended remains an unresolved challenge of the biological, social and cognitive sciences [22–24,26,31,33]. Computational models offer a particularly powerful tool for theory-building in this regard [37–41] and figure prominently in the literature on the evolution of technology [31,42–47]. However, as it currently stands, a strict separation exists between models focusing on the adaptive nature of technologies (e.g., [44,48–54]) and models focusing on the open-ended evolution of technological systems (e.g., [43,45,55,56]). Adaptive approaches often employ fitness landscapes [57–59] and model technological evolution as a process of cumulative optimization (see [15,22,31] for overview). Yet, despite the utility for investigating the evolution of technologies under the constraints of rich, high-dimensional spaces (e.g., [49,51,52]), the landscapes used in these models are bounded and of limited applicability to questions of open-endedness [37,59]. Conversely, models of open-ended evolution tend to explain the evolution of technology in terms of its cumulative and combinatorial propensities [43,45,55,56,60–62]. The explanatory goal here is to identify the conditions underpinning the long-term growth in the diversity and complexity of technological systems [43,45]. Missing from this approach is any explicit representation of the complex needs, problems and goals faced by societies and how these interact with technological systems in both constraining and enabling open-ended evolution.

To address these limitations, we develop a computational model that aims to investigate the long-term evolution of technology using a minimal set of processes and assumptions. Simplifying, our model abstracts away from individual-level interactions found in agent-based models [41], and models technological evolution at the macro-level [43,61]. In our model, the dynamics of technological evolution are conceived of as a co-evolutionary relationship between two fundamental processes: one which changes the structure of technological systems (the skills, techniques, knowledge and artifacts available to a society) and another which changes the structure of search spaces (the aggregate collection of needs, problems and goals of a society at a given point in time). By modelling technological evolution in this way, our model makes four contributions that link together the technological systems and search spaces of societies with the potential for open-ended evolution.

First, we explicitly represent search spaces alongside the technological systems of societies. Unlike previous models, where search spaces are either bounded (e.g., [50,52,53]), black boxed in favour of intrinsic utility/fitness values (e.g., [45,55,62]) or ignored altogether (e.g., [43,46,63]), we assume technological systems and search spaces are structured. This provides us with a way of modelling the structure of technological systems and search spaces as varying both in terms of their mutual fit as well as their complexity. In the context of our model, search spaces serve as an adaptive target that dynamically influence the adoption of changes to a technological system. These changes include modifications (that maintain complexity), simplifications (that decrease complexity) and expansions (that increase complexity). Importantly, this recognises that the structure of the search space is not inherently geared towards a progressive increase in complexity. Instead, search spaces can impose pressures to maintain or even simplify the complexity of technological systems.

Second, we propose that technological systems and search spaces are subject to cultural evolutionary dynamics. Needs, problems and goals are not static and invariant properties of the world, but rather form a dynamically shifting landscape which influences the direction of technological evolution. Although it is relatively uncontroversial to model technological systems as culturally evolving entities [8,43,64,65], we consider parallel dynamics are at play in changing the search spaces of a society [32,33,66]. Extending the logic of cultural evolutionary theory to search spaces naturally follows if we think of needs, problems and goals as a form of information that is socially transmitted [67]. In aggregate, this information determines what constitutes an effective system of technologies, and serves as an adaptive landscape to explore and exploit. Not only does this build upon the well-established notion that needs, problems and goals are cognitive phenomena [66,68,69], it also enables us to model search spaces as co-evolving with the technological systems of a society.

Third, co-evolutionary dynamics in our model follow a two-step process of generating and then adopting changes to both technological systems and search spaces. Crucially, this allows us to model co-evolution in terms of stochastic and deterministic factors. Stochastic factors, which are analogous to drift in biological evolution [70,71], assume random changes shape the evolutionary trajectory of technological systems and search spaces. In a purely stochastic scenario, technological systems and search spaces are maximally decoupled – the adoption of changes in one does not causally influence the adoption of changes in the other. Deterministic factors, which are analogous to selection dynamics [72] in biology or social learning biases [73] and selective filters [65] in culture, evaluate and adopt changes based on effectiveness: technological systems are refined to more effectively exploit search spaces, while search spaces are restructured to more effectively align with the technological capabilities of a society.

Fourth, in order to sustain the costs of changing both technological systems and search spaces, societies need to produce and then allocate resources at each generation to these two processes. Resource constraints are a feature of any system subject to computational and energy demands. Human societies are no different and must therefore produce, consume and allocate resources in order to maintain their activities [35,36,74,75]. Differences in the ability to produce resources lead to differences in the capabilities of societies to generate and adopt changes to technological systems and search spaces. Failure to procure sufficient resources is commonly associated with technological stagnation [76] and societal collapse [77,78], whereas surplus resources are critical for societies to overcome the costs of increased complexity [79] and to maintain long-term cumulative growth [75,80]. A key feature of our model is that resources can theoretically grow without limit so long as societies continually expand their search space and maintain effective technological systems.

Open-ended evolution in this context corresponds to a process of continually increasing the complexity of both technological systems and search spaces. The challenge facing societies is to maintain effective technological systems and engage in the ongoing expansion of the search space. Here, more complex search spaces have a greater potential to produce resources than simpler ones. Yet, to realise this potential, societies need to also adopt improvements to their technological systems. An inability to find effective outcomes is penalised by assuming the cost of maintaining technological systems scales with complexity. This represents the observation that supporting complex systems of technologies requires societies to solve complex problems associated with the production and consumption of resources [75,79–81]. We argue it is this co-evolutionary interaction between maintaining effective technological systems, the ongoing expansion of the search space and the increased provision of resources that underpins the open-ended evolution of human technology.

In the following, we manipulate the extent to which the co-evolutionary dynamics between technological systems and search spaces are stochastic or deterministic and examine in which conditions open-ended evolution emerges. Our findings suggest that the balance between stochastic and deterministic factors constitutes a fundamental limiting or enabling factor on the long-term sustainability of co-evolutionary dynamics. In particular, we show that in the vast majority of cases the co-evolutionary dynamics end up exhausting the available resources and hit an absorbing barrier [37]: a boundary condition on the ability of societies to generate and adopt changes to their technological systems and search spaces. Open-ended growth is comparatively rarer and only emerges when both technological systems and search spaces are shaped by sufficiently powerful selection pressures.

2. Model description: bitw0r1d

Bitw0r1d is a general framework for simulating the cultural evolution of technology. Adopting a macroscopic approach, which aims to explain long-term patterns of change using a minimal set of endogenous macro-level properties [43,61], we model the dynamics of technological evolution in terms of two causally interacting processes: one that changes the structure of technological systems (\mathbb{T}) and another that changes the structure of the search space (\mathbb{S}) (see Fig. 1).

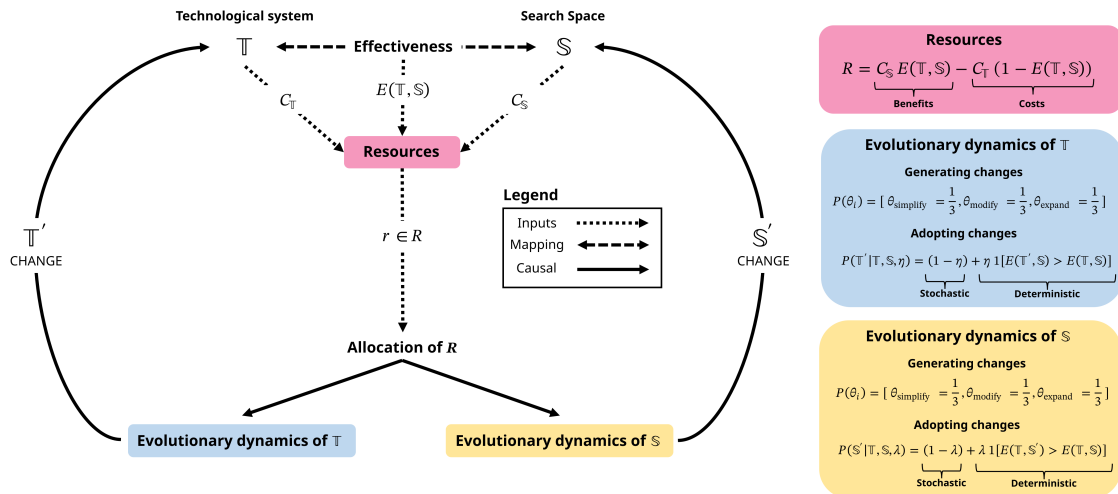


Figure 1. A diagram outlining the general dynamics of bitw0r1d. At each generation, a society needs to find effective mappings between \mathbb{T} and \mathbb{S} . The effectiveness of this mapping as well as the complexity of \mathbb{T} (C_T) and \mathbb{S} (C_S) determine the amount of resources (R). These resources are then allocated to two processes: one which changes the technological systems of a society and another which changes the underlying search space. We assume both processes follow a two-step cultural evolutionary dynamic of generating and adopting changes. Our model varies the selection pressures on \mathbb{T} and \mathbb{S} by manipulating the extent to which the adoption of changes are stochastic or deterministic: η controls the selection pressures on \mathbb{T} and λ controls the selection pressures on \mathbb{S} .

(a) Technological systems (\mathbb{T}) and search spaces (\mathbb{S})

At the start of a simulation, a society is initialised with a technological system (\mathbb{T}) and a search space (\mathbb{S}). Both \mathbb{T} and \mathbb{S} are operationalised as bitstrings of N -length (see [20,31,57,82] for similar approaches). Search spaces represent the aggregate collection of needs, problems and goals facing a society and determine what constitutes an effective system of technologies, whereas technological systems represent the totality of skills, techniques, artifacts and knowledge used to exploit these spaces. Modelling technological systems and search spaces as bitstrings captures two important properties. First, the distance between \mathbb{T} and \mathbb{S} determines the level of effectiveness, $E(\mathbb{T}, \mathbb{S})$. Second, we allow the string length of both \mathbb{T} and \mathbb{S} to vary, which serves as a proxy for complexity, $C_{\mathbb{T}}$ and $C_{\mathbb{S}}$.

Formally, effectiveness is measured using an inverted form of the normalised Levenshtein distance [83]:

$$E(\mathbb{T}, \mathbb{S}) = 1 - \frac{LD(\mathbb{T}, \mathbb{S})}{\max(C_{\mathbb{T}}, C_{\mathbb{S}})}, \quad (2.1)$$

where $C_{\mathbb{T}}$ and $C_{\mathbb{S}}$ refer to the string length of \mathbb{T} and \mathbb{S} respectively (see the next paragraph for more details), and $LD(\mathbb{T}, \mathbb{S})$ tells us the minimum number of single-edit changes (insertions, deletions and substitutions) required to transform one string into another. We use this metric to model the fit between technological systems and search spaces. Values of $E(\mathbb{T}, \mathbb{S}) \rightarrow 1.0$ approximate increasingly effective mappings of \mathbb{T} and \mathbb{S} , whereas values of $E(\mathbb{T}, \mathbb{S}) \rightarrow 0.0$ represent increasingly less effective ones. An optimal outcome is achieved when a system of technologies is equivalent to the structure of the search space, $E(\mathbb{T}, \mathbb{S}) = 1.0$, and a non-optimal configuration is when \mathbb{T} and \mathbb{S} are maximally distant from one another, i.e., $E(\mathbb{T}, \mathbb{S}) = 0.0$.

Complexity specifically refers to the string length of technological systems (denoted as $C_{\mathbb{T}}$) and search spaces (denoted as $C_{\mathbb{S}}$). Restricting our definition of complexity to string length allows us to formulate it in terms of computational principles, i.e., the time required (on average) to find a maximally effective outcome given an initial state and an underlying process (see supplementary for a fuller treatment of this point). Within the general constraints of our model, longer strings can be viewed as more complex than shorter ones because there are a greater number of possible configurations. On average, if we assume \mathbb{T} and \mathbb{S} are maximally distant from one another, i.e., $E(\mathbb{T}, \mathbb{S}) = 0.0$, then a $C_{\mathbb{T}} = C_{\mathbb{S}} = 20$ will require far fewer changes to find an optimal outcome than $C_{\mathbb{T}} = C_{\mathbb{S}} = 200$.

(b) Resources (R)

Evolutionary dynamics in our model are both constrained by and responsible for the production of resources. Differences in resources translate into differences in the ability of societies to engage in evolutionary dynamics. Specifically, the amount of resources determine the number of iterations ($i \in I$) at each generation, where a single iteration consists of either making changes to \mathbb{T} or making changes to \mathbb{S} .

We conceptualise this as a two-step process of first producing and then allocating resources. The production of resources (R) is governed by the interaction between $C_{\mathbb{T}}$, $C_{\mathbb{S}}$ and E (which denotes a simplified notation for effectiveness):

$$R(C_{\mathbb{T}}, C_{\mathbb{S}}, E) = \underbrace{C_{\mathbb{S}}E}_{\text{benefits}} - \underbrace{C_{\mathbb{T}}(1 - E)}_{\text{costs}} \quad (2.2)$$

where $C_{\mathbb{S}}E$ represents the benefits of effectively exploiting a search space and $C_{\mathbb{T}}(1 - E)$ captures any costs arising from ineffective technological systems. We make two main assumptions here. First, gains in resources are bounded by the complexity of the search space ($C_{\mathbb{T}}$), with $E(\mathbb{T}, \mathbb{S})$ determining how close a society is to realising this resource potential. This assumes more complex search spaces are associated with an increased resource potential. Second, the costs for ineffectiveness, $1 - E(\mathbb{T}, \mathbb{S})$, scale with the complexity of technological systems ($C_{\mathbb{T}}$). As technological systems grow in complexity, a society will incur increased costs if it is maintaining skills, techniques and artifacts that do not effectively contribute to the production of resources.

Following the production of resources, societies then allocate these to two mutually exclusive processes: one which changes the technological systems of a society and another that changes the underlying search space. As a simplifying assumption, resource allocation remains unbiased, i.e., $P_{\text{allocate}} \sim \text{Bernoulli}(0.5)$. This assumes there is no inherent preference for changing \mathbb{T} or \mathbb{S} . As such, the rate of change for technological systems and search spaces is approximately equivalent at each generation. See the supplementary for situations in which sampling from the Bernoulli distribution is biased.

(c) Cultural evolutionary dynamics (η and λ)

Cultural evolutionary dynamics are modelled as a two-step process of first generating and then adopting changes to both technological systems (\mathbb{T}) and search spaces (\mathbb{S}). For the generative component, we assume there are three possible options to change \mathbb{T} or \mathbb{S} : to remove a randomly chosen bit (e.g., *simplify*: 1011 \rightarrow 101), to flip a randomly chosen bit to its Boolean complement (e.g., *modify*: 1011 \rightarrow 1111) or to introduce a new randomly chosen bit at a randomly assigned position (e.g., *expand*: 1011 \rightarrow 10111). The choice of option always remains unbiased, i.e., $P(\theta_i) = (\theta_{\text{simplify}}, \theta_{\text{modify}}, \theta_{\text{expand}}) = (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$. Once a change is introduced, its adoption is contingent on whether the dynamics are stochastic or deterministic. For technological systems, the adoption of a change ($\mathbb{T} \rightarrow \mathbb{T}'$) at a given iteration is underpinned by the following:

$$P(\mathbb{T}' | \mathbb{T}, \mathbb{S}, \eta) = \underbrace{(1 - \eta)}_{\text{stochastic}} + \underbrace{\eta \cdot 1[E(\mathbb{T}', \mathbb{S}) > E(\mathbb{T}, \mathbb{S})]}_{\text{deterministic}} \quad (2.3)$$

where \mathbb{T} is the current technological system, \mathbb{T}' represents a proposed change to this system, and \mathbb{S} is the search space. η is a parameter $\in [0, 1]$ that allows us to manipulate the probability a change is adopted stochastically or deterministically.

If $\eta = 0.0$, then the evolution of the system is purely stochastic and reduces to $P(\mathbb{T}' | \mathbb{T}, \mathbb{S}, \eta) = (1 - \eta) = 1.0$, i.e., a change is adopted irrespective of whether or not it increases effectiveness. Conversely, for $\eta = 1.0$, the evolutionary dynamics are purely deterministic and the outcome depends on the indicator function $1[\cdot]$: here, if \mathbb{T}' is more effective for exploiting a search space, as denoted by $E(\mathbb{T}', \mathbb{S}) > E(\mathbb{T}, \mathbb{S})$, then \mathbb{T}' is adopted as the new state of the system at the next iteration. Otherwise, if $E(\mathbb{T}', \mathbb{S}) < E(\mathbb{T}, \mathbb{S})$ a society remains with the existing state of \mathbb{T} .

Intermediate values, $\eta = (0.0, 1.0)$, incorporate some mixture of deterministic and stochastic factors into the dynamics of adopting changes. As such, the structure of technological systems will to some extent reflect both randomly adopted changes as well as changes selected on the basis of improving effectiveness. Modelling the dynamics in this way assumes the adoption of changes is endogenous and incremental. A technological system culturally adapts inasmuch as the adoption of changes helps address the needs, problems and goals of a society.

Parallel dynamics hold for the evolution of search spaces:

$$P(\mathbb{S}' | \mathbb{T}, \mathbb{S}, \lambda) = \underbrace{(1 - \lambda)}_{\text{stochastic}} + \underbrace{\lambda \cdot 1[E(\mathbb{T}, \mathbb{S}') > E(\mathbb{T}, \mathbb{S})]}_{\text{deterministic}} \quad (2.4)$$

except λ now controls the stochastic and deterministic forces acting upon the adoption of changes to a search space (\mathbb{S}). Values of $\lambda \rightarrow 0.0$ increasingly adopt random changes to the search space, whereas values of $\lambda \rightarrow 1.0$ increasingly evaluate and adopt changes to \mathbb{S} that improve effectiveness. This means that search spaces culturally evolve by changing the needs, problems and goals of a society. Some of these changes are random and others are selected when $\lambda \in (0.0, 1.0]$. A search space culturally adapts by adopting changes that improve effectiveness, i.e., the needs, problems and goals are restructured to more effectively map onto the existing technological capabilities of a society.

We can think of different parameter values for $\eta \in [0, 1]$ and $\lambda \in [0, 1]$ as determining the extent to which technological systems and search spaces are coupled to one another and capable of co-evolution. Special cases hold at the extremes of the parameter space: purely stochastic dynamics ($\eta = \lambda = 0.0$) mean that technological systems and search spaces are solely driven by random changes and evolve independently of one another, while purely deterministic dynamics ($\eta = \lambda = 1.0$) are entirely driven by selection for effectiveness and constitute a perfect co-evolutionary relationship (see supplementary for more details).

In the following, we only consider $\eta \in (0, 1)$ and $\lambda \in (0, 1)$. This assumes there is always some degree of co-evolution between \mathbb{T} and \mathbb{S} and allows us to investigate a range of scenarios: from strongly stochastic ($\eta = \lambda = 0.01$) to strongly deterministic ($\eta = \lambda = 1.0$).

(d) Simulation runs

For the reported simulation runs, societies are initialised with randomly sampled technological systems and search spaces of $C_{\mathbb{S}} = C_{\mathbb{T}} = 2$ (minimum level of complexity is $C = 1$). Parameter combinations of $\eta \in (0, 1)$ and $\lambda \in (0, 1)$ consist of $K_{\text{sim}} = 1000$ simulations. A simulation halts under one of three conditions: (i) the maximum number of generations is reached ($\max_g = 10,000$), (ii) the upper-bound of technological complexity is either matched or exceeded ($\max_{C_{\mathbb{S}}} \geq 10,000$), or (iii) societies hit an absorbing barrier having exhausted their resources ($R \leq 0$).

For (iii), we assume that absorbing barriers only come into effect after societies have exhausted an initial resource endowment ($R_{\text{endow}} = 100$). Introducing an endowment provides a warm up period for the dynamics and mitigates the initial conditions from too strongly influencing the outcomes (see supplementary for different initial endowments). Societies only draw upon this endowment when $R \leq 0.0$. If this endowment is exhausted, $R_{\text{endow}} \leq 0$, a society is no longer buffered against absorbing barriers and the dynamics will terminate at the next generation.

(e) Code availability

All code, data and supplementary material for reported runs are available from the following repository: <https://github.com/j-winters/bitw0rld>.

3. Results

A general finding of our model is that absorbing barriers represent the majority outcome across all parameter configurations (see Fig. 2). Without resources, a society cannot make changes to either its technological system or search space. In total, $\approx 98\%$ of simulation runs terminated as a result of an absorbing barrier, suggesting this constitutes a hard constraint on the emergence of open-ended growth. Of these, runs that most successfully avoided absorbing barriers corresponded to $\eta = 0.95$ and $\lambda = 0.80$ ($\approx 11.4\%$ reaching 10,000 generations) while the runs with the highest average survival rate are found at $\eta = 0.99$ and $\lambda = 0.99$ (reaching an average of ≈ 3060 generations).

The likelihood of hitting an absorbing barrier increases as the dynamics become increasingly stochastic. At one extreme of the parameter space ($\eta = \lambda = 0.01$), all simulation runs terminate as a result of absorbing barriers. Similar findings hold even when lowering the degree of stochasticity (e.g., $\eta = 0.2$ and $\lambda = 0.6$). In these cases, excessive stochasticity causes \mathbb{T} and \mathbb{S} to evolve relatively independently of one another, with changes largely following a random walk. This quickly results in collapse as societies are unable to discover effective outcomes and produce a net gain in resources.

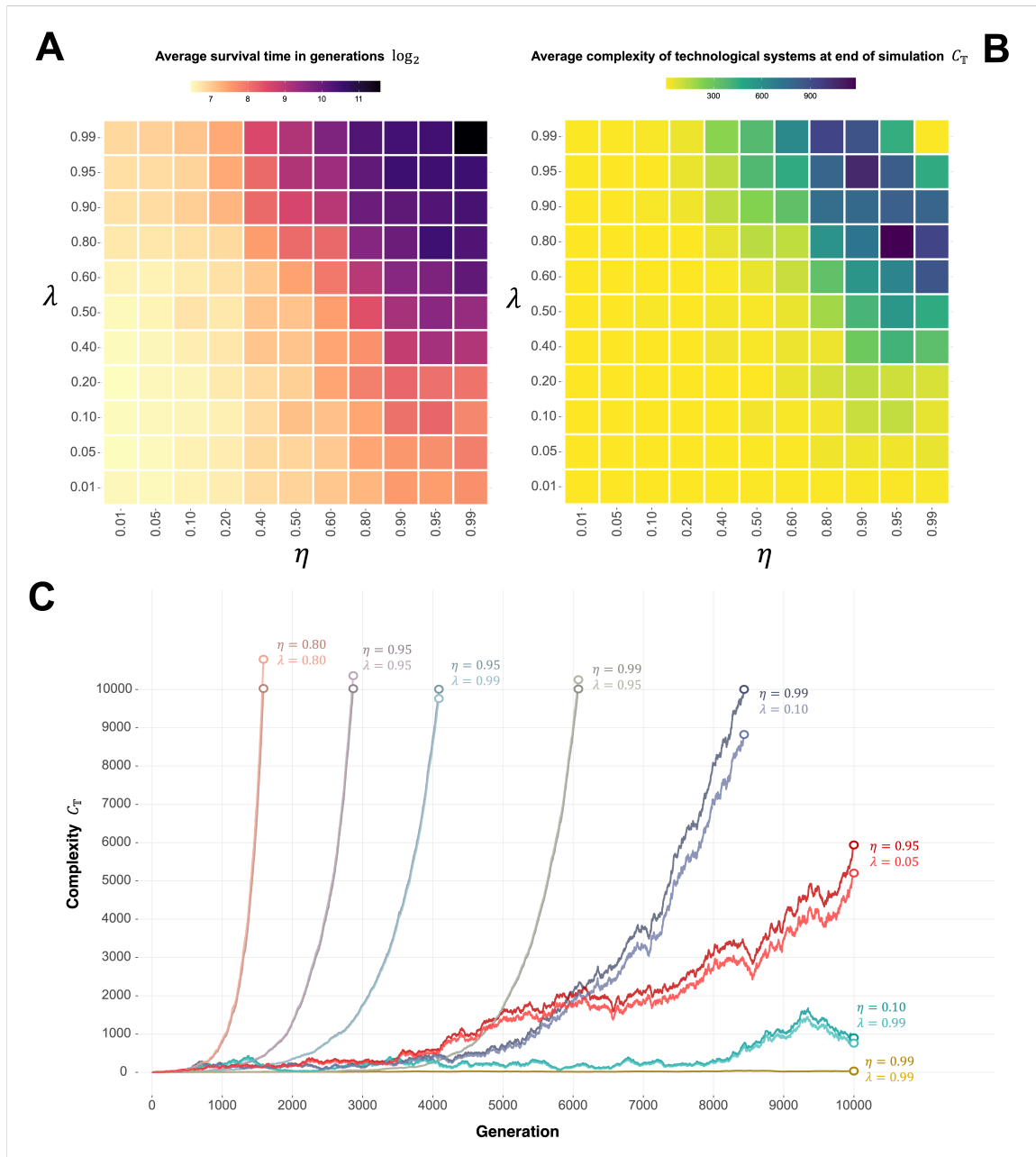


Figure 2. **A:** A heatmap showing the average survival time (\log_2) for all simulation runs across η and λ (note that runs which exceeded $C_T = 10,000$ were treated as reaching the full 10,000 generations). **B:** A heatmap showing the average complexity of technological systems (C_T) for all simulation runs across η and λ . **C:** Selected simulation runs showing a range of dynamics. Coloured lines represent the complexity of technological systems (denoted with η) and search spaces (denoted with λ) for different simulation runs.

At the other extreme ($\eta = \lambda = 0.99$), stronger selection pressures are more capable of sustaining co-evolutionary dynamics, but many simulation runs remain trapped in low complexity states for \mathbb{T} ($\mathbb{E}[C_T] = 10.79$) and \mathbb{S} ($\mathbb{E}[C_T] = 10.76$). This is due to the co-evolutionary dynamics maintaining a tight coupling where the adoption of changes in \mathbb{T} are made in reference to improving effectiveness for \mathbb{S} , and vice versa. We can think of this in terms of emergent local optima that confine the dynamics to simple technological systems and search spaces. For the majority of runs, the dynamics will either remain in these simple states or hit an absorbing barrier. However, as Fig. 3 illustrates, a minority do manage to escape and undergo open-ended growth ($\max_{C_T} = 2979$ at generation 10,000).

Avoiding absorbing barriers is also possible when one process is strongly deterministic ($\eta = 0.99$) and the other is strongly stochastic ($\lambda = 0.01$). This creates a moving target where the deterministic adoption of changes in one process tracks the stochastic changes of the other. Simulation runs in these instances are capable of reaching 10,000 generations, but stochastic nature of the dynamics means we cannot definitively state for a given simulation run whether \mathbb{T} and \mathbb{S} will keep co-evolving indefinitely or eventually hit an absorbing barrier (see Fig. 3). Long-term sustainability in such circumstances somewhat depends on the complexity of \mathbb{T} and \mathbb{S} . Reaching more complex states is advantageous inasmuch as a single adverse change represents a proportionally smaller reduction to the overall effectiveness. Crucially, this robustness-enhancing effect of complexity only holds when deterministic factors are present and strong enough to act as a countervailing force: here, adopting changes that improve effectiveness counteract stochastic perturbations, preventing drift-like dynamics from dramatically depleting the resources available to a society.

Notably, important differences exist depending on whether these stronger selection pressures are applied to technological systems (e.g., $\eta = 0.99$; $\lambda = 0.01$) or search spaces (e.g., $\eta = 0.01$; $\lambda = 0.99$). As Fig. 3 demonstrates, stronger selection pressures for technological systems result in high levels of sustainability and more complex outcomes than when similarly powerful selection pressures are applied to search spaces. This asymmetry is largely driven by our formulation of the resource function. While strong selection pressures on \mathbb{T} help mitigate any excess costs and track changes to \mathbb{S} , weak selection pressures on \mathbb{T} are especially costly when a random change that lowers effectiveness also increases the complexity of \mathbb{T} .

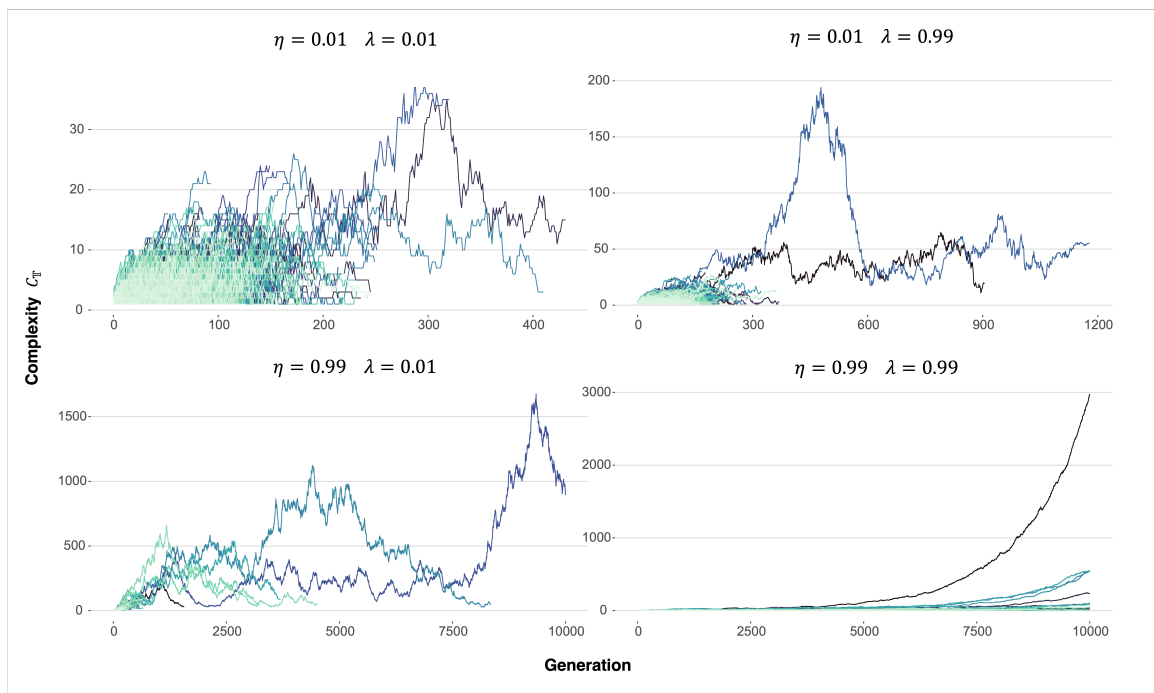


Figure 3. All simulation runs (coloured lines) showing the complexity for technological systems (C_T) for $\eta \in [0.01, 0.99]$ and $\lambda \in [0.01, 0.99]$. Note that the axes vary between facets of different parameter values. When $\eta = 0.01$, none of the runs manage to survive for the full 10,000 generations and are restricted to relatively simple technological systems. By contrast, when $\eta = 0.99$, a minority of runs manage to reach the full 10,000 generations, with $\eta = 0.99$ and $\lambda = 0.99$ exhibiting open-ended growth.

A critical threshold exists in our model where the dynamics transition to an open-ended regime. At this point, simulation runs either reach the full 10,000 generations or exceed the upper-limit of the simulation ($C_T = 10,000$). Different parameter combinations of η and λ influence the timing, frequency and rate of this growth (see Fig. 2C and top row of Fig. 4). For some runs, open-ended evolution is late emerging, extremely rare and slow growing (e.g., Fig. 2C for $\eta = 0.95$ and $\lambda = 0.05$) whereas other runs are early emerging, more common and undergo accelerated growth (e.g., Fig. 2C for $\eta = 0.80$ and $\lambda = 0.80$). Minimally, for simulation runs across all relevant parameter values, the emergence of open-ended evolution depends on three general conditions.

First, the dynamics exist in a far-from-equilibrium state, resulting from a balance of stochastic and deterministic factors. Specifically, the parameter values most conducive to open-endedness are those where stochastic factors play a prominent role in shaping both \mathbb{T} and \mathbb{S} , but are generally weaker than deterministic ones, e.g., compare $\eta = 0.40$ and $\lambda = 0.40$ with $\eta = 0.90$ and $\lambda = 0.90$ (see top row of Fig. 4). Having some degree of stochasticity prevents the dynamics from settling into a stable equilibrium, while the presence of strong selection pressures helps maintain effectiveness in the face of these stochastic perturbations (see bottom row of Fig. 4).

Second, in this far-from-equilibrium state, selection is strong enough to preferentially adopt expansionary changes. Although the generation of changes is equiprobable, with $P(\theta_i) = 1/3$, there are many more ways to expand \mathbb{T} or \mathbb{S} . A greater diversity of states means that on average there is a greater chance of discovering an effective outcome via expansion than via modification

or simplification. As a result, we should expect a net growth in complexity when (i) stochastic factors continually perturb the dynamics and open up the possibility for improving effectiveness (see previous paragraph), and (ii) there are sufficient resources to discover and adopt expansionary changes (see next paragraph).

Third, discovering these expansionary changes requires a society increases its production of resources. In low complexity states, the advantages of expansion can remain masked due the scarcity of resources. Fewer resources translates into fewer evolutionary opportunities to change \mathbb{T} or \mathbb{S} . As a consequence, the likelihood of discovering a beneficial expansion is constrained by the probability of generating this type of change in the first place. However, as the dynamics transition to more complex states for \mathbb{T} and \mathbb{S} , gains in resources increase the number of iterations, which, in turn, amplifies the chances of adopting expansionary changes. Under the right conditions, this causes open-ended growth to accelerate and exceed the upper-limit of our simulation (i.e., $C_{\mathbb{T}} \geq 10,000$).

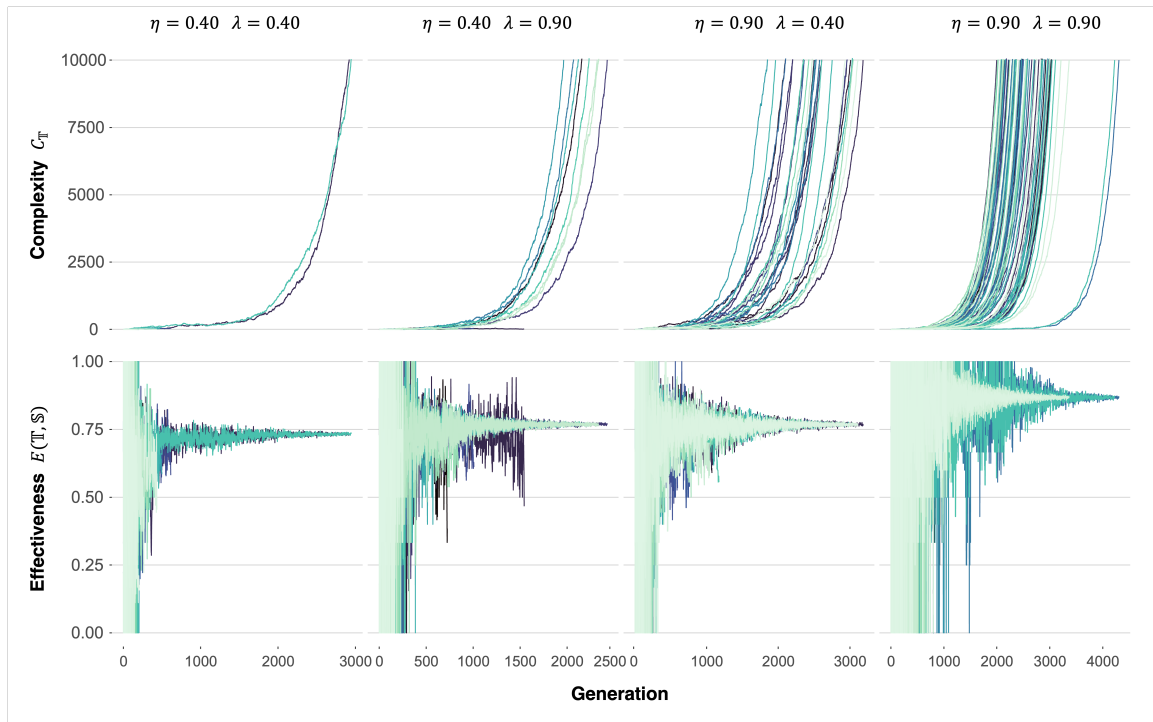


Figure 4. **Top row:** All simulation runs (coloured lines) showing the complexity of technological systems ($C_{\mathbb{T}}$) for $\eta \in [0.4, 0.9]$ and $\lambda \in [0.4, 0.9]$. **Bottom row:** The same simulation runs, but showing the level of effectiveness reached, $E(\mathbb{T}, \mathbb{S})$.

4. Discussion

Our paper started from a relatively simple premise: that *technological systems* (\mathbb{T} , the skills, techniques, knowledge and artifacts available to a population) and *search spaces* (\mathbb{S} , the aggregate collection of needs, problems and goals facing a society) co-evolve with one another. Unlike previous macro-level models, which focus solely on explaining the evolution of technological systems and abstract away from explicitly representing search spaces, we modelled technological systems and search spaces as culturally evolving entities that are shaped by a mixture of stochastic and deterministic factors. In our model, adopting changes not only impacts the mutual fit between technological systems and search spaces, it also leads to changes in structure that expand, maintain or reduce complexity. By manipulating the extent to which the adoption of these changes is stochastic or deterministic, we investigated the conditions in which co-evolutionary dynamics are sustainable and lead to the emergence of open-ended evolution.

Modelling \mathbb{T} and \mathbb{S} as co-evolving forces us to think seriously about processes that are typically idealised away and placed in a black box. A key contribution here is to link the underlying co-evolutionary dynamics to the costs and benefits of producing resources. Two routes exist in our model for increasing the resources available to a society: by improving the effectiveness of technological systems or through expanding the search space. We show that both routes are only possible under sufficiently strong selection pressures. Although maintaining a certain level of effectiveness is necessary for minimising the costs of supporting a complex technological system, open-ended growth only emerges when there is a sustained expansion of the search space. Search spaces play a critical role in this sense because they serve as an upper-limit on the maximum resource potential. Conceptually, expansion can be thought of as recognising and selecting needs, problems and goals associated with gains in resources. This is clearly a simplification in that the adoption of new needs, problems and goals is not strictly concomitant with increases in

resources. Nevertheless, it is also the case that resources are an ultimate constraint on technological progress [60], which suggests that any long-term expansion has to eventually resolve issues concerning computational and energy demands [35,36,74,79].

The co-evolutionary dynamics in the model are sensitive to the selection pressures acting on both technological systems (η) and search spaces (λ). The strength of these pressures is determined by the relative balance of stochastic and deterministic factors. As such, we can think of η and λ as a map of where co-evolutionary dynamics are and are not sustainable in the long-term. At one extreme, in regions dominated by stochasticity (e.g., $\eta = \lambda = 0.01$), an inability to produce resources very quickly leads to an absorbing barrier: a boundary condition on the ability of societies to generate and adopt changes to both their technological systems and search spaces. Our findings here place a very clear limit for explanations that rely on stochasticity as a primary driver of open-endedness [84,85] and contribute to wider debates over the role of neutral models in cultural evolution [86–88]. We show that in a mutualistic co-evolutionary scenario, where survival is contingent on the coupling of co-evolving entities, any factor that causes a decoupling runs the risk of collapse. Stochasticity is a relevant contributing factor, but only when it exists alongside strong selection pressures that help maintain effectiveness.

Minimally, open-ended growth is only possible so long as stochastic factors keep the co-evolutionary dynamics in a far-from-equilibrium state, and deterministic factors lead to the increased adoption of expansionary changes. Regions of the parameter space most conducive to open-ended growth are therefore characterised by significant selection pressures on technological systems *and* search spaces. Here, co-evolutionary dynamics play a compensatory role: technological systems adapt to the structure of search spaces and search spaces adapt to the structure of technological systems. There are many possible parameter combinations that give rise to open-ended growth in this respect. We suggest that the most plausible route is one in which the selection pressures are gradually increasing in both technological systems and search spaces. Not only does this account provide a gradualistic pathway to emergence, as the values of η and λ make it easier to traverse from unsustainable to sustainable co-evolutionary dynamics, it also corresponds to regions of the parameter space where open-ended growth is most likely to undergo progressive acceleration.

Accelerated growth is arguably the defining characteristic of the last few centuries of scientific, technological and economic progress [45,60,89–91]. Growth accelerates in our model when there are sufficient resources to search for and discover beneficial expansions. A subtle difference between our model and others is that we show how the advantages of expansion can remain masked when selection is weak for one process (e.g., $\eta = 0.99$ and $\lambda = 0.01$). Unmasking this advantage, then, requires stronger selection pressures shaping both technological systems and search spaces (e.g., $\eta = 0.40$ and $\lambda = 0.40$). It is only under these stronger selection pressures that the co-evolutionary dynamics are powerful enough to overcome initial resource limitations and to increase the number of opportunities to generate and adopt expansionary changes that improve effectiveness. Analogous constraints exist in cultural evolutionary models where differences in the effective population size of a society impacts its ability to generate and select adaptive cultural traits [44,92]. An advantage of our approach is that differences in resources are not limited to demographic factors, but could also vary due to the availability of cognitive technologies for processing information [33,93] (e.g., societies with and without writing systems) as well as the utilisation of energy sources [36,79] (e.g., societies which can and cannot harness the energy potential of coal).

Like all models, which are always wrong and sometimes useful [94], our model relies on several theoretical and methodological simplifications. Some possible critiques here concern the existence of an initial resource endowment, the linear relationship between search space complexity and its resource potential, and the assumption that resource allocation is unbiased. First, to help avoid absorbing barriers, we assume societies start out with an initial resource endowment ($R_{\text{endow}} = 100$). Methodologically, our choice of $R_{\text{endow}} = 100$ is a convenient simplification, which avoids the initial conditions from too strongly constraining the dynamics (see the supplementary for different resource endowments). Theoretically, we should expect societies to have access to some initial resources that are potentially non-renewable and susceptible to depletion. For example, during the Pleistocene we know there was an abundance of megafauna, with technological regressions and advancements linked to the overexploitation of these resources [90,95]. Societies can therefore temporarily exceed their natural carrying capacity by drawing upon excess resources. The challenge is to either develop sustainable practices before exhaustion or culturally adapt via the co-evolutionary dynamics.

Our second assumption is that the complexity of a search space forms a linear relationship with its resource potential: each additional expansion of \mathbb{S} yields a unit increase in the maximum obtainable resources (e.g., a $C_{\mathbb{S}} = 10$ produces a maximum of $R = 10$ whereas a $C_{\mathbb{S}} = 100$ produces a maximum of $R = 100$). Relaxing this assumption, to consider a greater diversity of resource functions, would allow us to model situations where search spaces of the same complexity differ in their maximum resource potential. By incorporating such extensions, future work could manipulate the extent to which resource functions form smooth (adjacent search spaces share similar resource functions) or rugged distributions (adjacent search spaces have different resource functions). This represents a tantalising prospect for bridging the tunable topologies of N/K fitness landscapes [37,57] and the open-ended search spaces of bitw0r1d. Navigating these topologies would likely lead to a greater variety of dynamics and could help us understand the situations in which open-ended growth undergoes long-term stagnation [96,97].

A third assumption pertains to the unbiased allocation of these resources. Maintaining an equitable distribution of resources assumes societies always have an equal chance of changing their technological systems or search spaces. This essentially builds-in a resolution to any explore-exploit dilemmas faced by a society when allocating its resources [98–100]. However, we do not know if this represents an optimal allocation strategy, and neither do we know whether societies are capable of reaching this balanced allocation in the first place. A more sophisticated model could treat societies as Bayesian learners [101] that dynamically update how resources are allocated. Different priors would represent different initial resource allocation strategies, i.e., hypotheses over

allocating resources to changing \mathbb{T} or \mathbb{S} . Learning would then be represented as a process of updating these priors by testing different allocation strategies and seeing if this improves effectiveness and/or increases the production of resources. Modelling resource allocation in such a way would allow us to both investigate the feasibility of reaching a balanced allocation as well as observe if skewed allocation strategies converge on sustainable co-evolutionary dynamics.

A fourth and final assumption is that societies do not interact. Indeed, in our model, each simulation run had only one evolving society. To some extent, this assumption could be taken to represent the entirety of human civilization, but it does overlook the richer dynamics of modelling societies as entities that interact with one another through competition (e.g., warfare) and cooperation (e.g., trade) over resources [102]. A more ambitious extension in this vein would model multiple societies via a fission-fusion process [103,104]. Societies could now proliferate over time by branching off from one another (fission), homogenise by integrating into larger civilizations (fusion), as well as collapse and disappear through processes already modelled in this paper (i.e., absorbing barriers). Future research is now well-positioned to link each of these processes to the ability of societies to develop effective and complex technological systems, to exploit and expand their search spaces, and to produce and allocate resources.

5. Conclusion

Any theory of human technological evolution, which seeks to explain its cumulative, adaptive and open-ended nature, needs to account for the relationship between technological systems (\mathbb{T}) and the changing needs, problems and goals of societies (what we termed search spaces, \mathbb{S}). Our model tentatively provides the stepping stones for such a theory by positing that \mathbb{T} and \mathbb{S} are subject to cultural evolutionary dynamics and capable of co-evolving with one another. Crucially, we formulated the relationship between \mathbb{T} and \mathbb{S} in terms of their ability to produce resources. This sets up a non-trivial challenge for the dynamics of our model: societies need to overcome the resource costs of maintaining complex technological systems by finding effective outcomes *and* to continually increase their access to resources through the expansion of the search space.

By controlling the extent to which the co-evolutionary dynamics are stochastic or deterministic, our model arrived at three general conclusions. First, sustaining long-term co-evolution is difficult when societies need to produce resources, with absorbing barriers representing a hard constraint on the emergence of open-ended growth. Second, open-ended growth is possible so long as stochastic factors keep the dynamics in a far-from-equilibrium state, and deterministic factors increasingly adopt expansionary changes. Third, regions of the parameter space most conducive to open-ended growth are those characterised by significant selection pressures on both \mathbb{T} and \mathbb{S} . Understanding long-term technological evolution is therefore going to require a fully articulated theory of how technological systems and spaces co-evolve over time.

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