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The Cultural Evolution of Medical Technologies

A Model of Sequential Treatments in the Medical Setting

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Abstract
When people get ill, they naturally want to restore health through medical interventions. Here I model a situation in which individuals can psychologically entertain multiple potential treatments at once: when illness occurs, individuals would attempt one treatment first, and if it fails to produce an observable effect within a particular time period, a second treatment is attempted, and the eventual recovery is attributed to the treatment that is temporally closer. This creates population dynamics wherein the therapeutic power of the superior/effective medical treatments is misattributed to inferior/ineffective treatments. Through both analytic formulation and agent-based simulation, I show that the equilibrium frequencies of different treatment variants depend on their natural variability in the effect timing, the level of individual patience, and the number of cultural models sampled by the naive individual. Both ineffective and effective medical treatments may stably coexist in the population under a range of parameter settings.

Keywords Cultural evolution · Traditional medicine · Cognition · Agent-based simulation

Across cultures and throughout history, one recurrent phenomenon in human societies is the use of ineffective medical treatments. Early pioneering work in anthropology has pointed out that the conception of illness and the corresponding treatments in traditional populations are drastically different from those in modern medical science (Ackerknecht, 1942; Clements, 1932). Specifically, illnesses are often believed

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to be caused by spiritual agents (Murdock, 1980) or by an imbalance of bodily elements such as the humoral theory in ancient Greece and Rome (Javier, 2014) and the *yin-yang* theory in traditional China (Wang, 2014). From a modern scientific perspective, treatments based on these traditional theories such as appeasing spiritual agents through offerings and sacrifices and restoring the balance of bodily elements through bloodletting, are unlikely to have real therapeutic effects beyond the placebo effect.[1] It should be noted that these practices are not only a relic of the past: many ineffective treatments still prevail in contemporary modern societies under the umbrella category "alternative medicine." For example, a representative survey conducted in south Australia shows that more than 50% of the respondents used at least one non-prescribed alternative medicine in the year 2000 (MacLennan et al., 1996), and a similar survey conducted in the US shows that nearly 4 out of 10 adults used complementary or alternative medicine in 2007 (Barnes et al., 2009).

What, then, might explain the prevalence and persistence of these ineffective medical treatments? Cognitive and evolutionary-minded researchers have attempted to address this question from a few angles. Broadly, these efforts can be grouped into two categories. First, certain treatments may be subjectively perceived as efficacious because they appeal to evolved cognitive mechanisms such that instrumental practices with specific features appear to be intuitively plausible (Claidière & Sperber, 2007; Sperber, 1996). The cultural success of bloodletting, for example, has been attributed to its intrinsic plausibility based on folk biological intuitions (Miton et al., 2015). Second, treatments may be perceived as efficacious because the outcome information of these treatments is obtained and processed in biased ways. From the perspective of individual cognition, the placebo effect (the expectation that a treatment will be efficacious increases its therapeutic effect; Kaptchuk & Miller, 2015) and "regression to the mean" (illness symptoms will get better regardless of the application of the treatment; Barnett et al., 2005; Linden, 2013) often lead to erroneous causal inferences regarding the genuine efficacy of medical treatments. From the perspective of cultural transmission, since the efficacy information of many medical treatments is culturally obtained, transmission biases such as prestige bias (Henrich & Gil-White, 2001) and conformist bias (Henrich & Boyd, 1998) may favor a treatment that is practiced by prestigious individuals or is already prevalent in the population for non-efficacy-related reasons. Additionally, psychological and social factors such as the under-reporting of negative evidence (de Barra, 2017; de Barra et al., 2014) may bias the transmission process and lead to an overestimation of the efficacy of these treatments (Hong, 2022a; Hong & Henrich, 2021; Hong, Slingerland & Henrich, 2023).

It is important to note that these are not exclusive explanations (Miton et al., 2015), and they are often used to answer different types of questions. For example, intuitive plausibility explanations help us understand why medical practices with certain features are preferred rather than others, whereas explanations that invoke

[1] Of course, the placebo effect itself may serve as a potent factor that sustains many ineffective (by modern standards) traditional medical practices. See Hong (2021) for a detailed examination of the role of the placebo effect in the cultural evolution of medical technology.

contextual factors (transmission biases, social factors such as under-reporting of negative evidence) may help elucidate population-level mechanisms that sustain ineffective practices once they already exist in the population. A complete understanding of the ineffective medical practices is surely going to include most, if not all, of the above cognitive, psychological, and social factors.

So far, the mechanisms via which ineffective technologies can be maintained in the population are domain general and apply to any instrumental practices. However, medical treatments differ from many other practices in that their effects are often not immediately observed. In other words, it often takes some time for the treatment to take observable effect. In the causal cognition literature, temporal contiguity is an important aspect of human causal attribution (Shanks et al., 1989; Vallée-Tourangeau et al., 2005), especially when individuals have no strong theoretical reason to expect a delay in the observing causal effects (Buehner & May, 2003; Le Pelley et al., 2017). As such, treatments that take too long to come into effect may not be viewed as the cause of the recovery. Another characteristic of medical treatments is that more than one treatment may be attempted if the patient does not recover from the illness in time. In modern medical settings, for example, many people are willing to try alternative medicine and healing methods when conventional treatment fails (Kantor, 2009; Vohra et al., 2005). My own fieldwork in southwest China among the Nuosu also reveals that many individuals who engaged in traditional healing practices did so after receiving standard treatment in local hospitals but failed to observe any improvement (Hong, 2022b).[2] This means that if people observe illness recovery, they are much more likely to attribute it to the second treatment (traditional healing) than the first treatment (modern medicine). In fact, field interviews show that people frequently emphasize the empirical success of traditional healing practices and would only acknowledge that they first went to the hospital when probed specifically by the interviewer.

An important consequence of this type of causal inference based on temporal proximity is that the first attempted treatment suffers a disadvantage regarding its perceived efficacy because, when both treatments are applied, the one that is temporally closer to the recovery (even if ineffective) gets the credit. This creates an interesting negative feedback loop wherein an ineffective treatment and a genuinely effective treatment may coexist: the genuinely effective treatment may be perceived as more efficacious for a variety of reasons, yet precisely because it is perceived as more efficacious, people attempt it first, and as a result, the eventual recovery may often be attributed to the ineffective treatment that is attempted later. In other words, when a medical treatment is genuinely effective but takes some time for the effect to occur, an inferior treatment may be erroneously inferred as effective when people are not sufficiently patient.

[2] Granted, it is possible that some of these traditional healing practices do have some genuine therapeutic effect. The point here is that the treatment that is tried second usually gets the credit, no matter the efficacy.

Analytical Model

Here, I use a formal modeling approach to examine this possibility closely. Specifically, I assume that individuals can psychologically entertain multiple treatment variants and investigate the general phenomenon where a superior technology and an inferior technology may coexist in the population because of sequential treatments and causal attribution based on temporal contiguity. As such, the puzzle of the retention of ineffective medical treatments will be a special case of this general model where the therapeutic effect of the inferior treatment is the same as or worse than chance recovery. In other words, although in the model all treatments are technically "effective" (the only difference being some are fast-acting and others slow-acting), genuinely ineffective treatment could be viewed as a treatment with recovery time the same as spontaneous/natural recovery, and as such the analyses below focus on the type of illness that will recover naturally; in other words, the patient's health will eventually be restored regardless of the treatment intervention applied. In such a setting, a superior treatment would be one that significantly speeds up the recovery process; an inferior treatment would be one that only marginally increases the recovery process; and a genuinely ineffective treatment would be one that does not affect the natural recovery timing (or perhaps even lengthens it). In the following sections, "ineffective" and "inferior" will be used interchangeably since the overall question to be addressed remains the same—the investigation of the conditions and mechanisms under which better treatments do not outcompete worse ones.

To do so, I first present an analytic formulation of the basic dynamics and equilibria of the frequency of cultural variants and then use agent-based simulation to explore frequency changes of various types of individuals in more realistic settings. In particular, I look at whether one treatment variant may reach fixation or be genuinely "lost" in the population. Since this model explicitly focuses on the temporal dimension of the effect of medical treatments, treatment efficacy is defined as the time it takes for some medical treatment to take effect. Therefore, superior treatments refer to treatments that take effect quickly after being applied. I assume that the time it takes for an effect to occur follows some distribution (hereafter referred to as "effect timing distribution"). In the epidemiological literature, a number of distributions have been proposed (Krylova & Earn, 2013; Lloyd, 2001), and for the sake of mathematical convenience a normal distribution is used throughout this paper,[3] meaning that when a treatment is applied to cure some illness, the time it takes for the effect to occur is a normal random variable with parameters μ and σ. Further, I assume that individuals have a "patience threshold" denoted by s, which refers to the amount of time an individual is willing to wait before switching to a different treatment. Causal attribution is entirely dependent on relative temporal contiguity: that is, individuals will attribute the recovery to the treatment whose timing of application is temporally closer to the recovery (hereafter "treatment effect," "effect," and "recovery" will be used interchangeably).

[3] The choice of normal distribution here also has some empirical support: for example, the recovery time for COVID-19 roughly follows a normal distribution with a mean of 18 days and standard deviation of 13 days (Liu et al., 2021; also personal communication with Liu in October 2021).

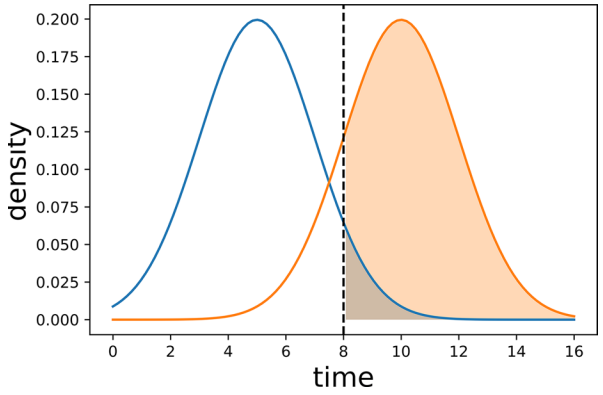

Fig. 1 A graphical example of the probability density functions of two normal distributions representing the proportion of people who try the first treatment (blue for T1, orange for T2) and do not observe effect within s time (denoted by the black dashed line), thus attempting the other treatment. Shading represents the amount of proportion of people who attempt T1 or T2 but do not observe a treatment effect within s time (orange-blueish for T1, orange for T2). Parameter values: $\mu_1 = 5, \sigma_1 = 2, \mu_2 = 10, \sigma_2 = 2, s = 8$

Figure 1 provides a graphical illustration of the probability density function of effect timing of two treatments with different means but the same standard deviation and patience threshold. From an individual's perspective, Fig. 1 can be viewed as the probability of recovery at a particular time after taking treatment 1 (hereafter T1) or treatment 2 (hereafter T2). From a population perspective, the integral between two time points can also be viewed as the expected proportion of individuals who take T1 or T2 and recover within that time period. In this figure, a patience threshold $s=8$ is denoted by the black dashed line, and the area under the curve to the right of $s=8$ and the two probability density functions thus can represent the proportion of people who attempt T1 or T2 but do not observe a treatment effect within s time (orange-blueish for T1, orange for T2). In this example, while most individuals who apply T1 will observe a treatment effect within s, a relatively small proportion of people who apply T2 will observe a treatment effect within s since the mean recovery time for T1 ($\mu_1=5$) is shorter than that for T2 ($\mu_2=10$).

Analytic Formulations of Population Dynamics

Assuming there are two treatment variants in the population, the cumulative density function of the effect timing distribution must be computed in order to model the population dynamics of treatment frequency change. Recall that the cumulative density function for the standard normal distribution $\phi(x)$ is

$$\phi(x) = P(Z \leq x) = \frac{1}{2}\left[1 + erf\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right] \quad (1)$$

Where *erf* denotes the error function (Levi, 2019) and $\phi(x)$ is the probability that the random variable takes a value less than or equal to x. In our medical treatment

setting, $\phi(x)$ thus represents the proportion of individuals who apply a treatment and recover within x time.[4]

More generally and conveniently, the cumulative density function of any normal distribution with parameters μ and σ may be denoted as $\phi\left(\frac{s-\mu}{\sigma}\right)$. Let the proportion of individuals who try T1 first be p and the mean and standard deviation of T1's effect timing distribution be μ_1 and σ_1, respectively; we can now formally represent the proportion of individuals who observe the effect of T1 within time s as

$$p \cdot \phi\left(\frac{s-\mu_1}{\sigma_1}\right)$$

Similarly, the proportion of individuals who try T2 first and observe its effect within time s can be represented as

$$(1-p) \cdot \phi\left(\frac{s-\mu_2}{\sigma_2}\right)$$

The next step is to model the transmission of T1 and T2 over generations. The rich literature in cultural evolution has both theoretically and empirically examined the transmission rules of cultural variants (Boyd & Richerson, 1985; Kendal et al., 2009; Muthukrishna et al., 2016; Vale et al., 2017). Note that our medical treatment case is different in that when individuals adopt a treatment, they will attempt that treatment first and will resort to the other treatment when the first treatment takes too long to take effect. In other words, even when people "adopt" one treatment, they will still be aware of the alternative treatment. In later sections I will deal with the possibility that individuals may not even be aware of the existence of alternative treatments.

Here we examine two possible transmission rules. For the first type, naive individuals may adopt a treatment to use initially based on its perceived efficacy in the parental generation. Specifically, a naive focal individual may sample a number of models, "ask" each model which treatment they think is effective, and then make an adoption decision based on the relative proportion of models who reported either T1 or T2. In the rest of the paper, this transmission rule will be termed "belief-based copying," which bears some resemblance to payoff-biased transmission in the cultural evolution literature (Kendal et al., 2009). In the simplest case, the proportion of individuals in the offspring generation trying T1/T2 first would be the same as the proportion of individuals in the parental generation who believe that T1/T2 is effective. This type of transmission is reminiscent of the "proportional imitation" in economics (Schlag, 1998) and cultural evolution (Baldini, 2012), although in this case the payoffs of T1 and T2 cannot be directly evaluated and are inferred from the relative proportion of individuals who causally attribute their recovery to T1/T2. With

[4] This is in fact an approximation since $\phi(x)$ also includes the area where x has negative values, and time obviously cannot be negative. However, this area is usually quite small and therefore does not qualitatively change the result of the subsequent analysis.

the above notation scheme, the proportion of individuals in the original (parental) generation who attribute their recovery to T1 is thus

$$p_{T1\text{effective}} = p \cdot \phi\left(\frac{s-\mu_1}{\sigma_1}\right) + (1-p) \cdot \left(1 - \phi\left(\frac{s-\mu_2}{\sigma_2}\right)\right) \quad (2)$$

where $p \cdot \phi\left(\frac{s-\mu_1}{\sigma_1}\right)$ represents the proportion of individuals who attempt T1 first and recover within s time, and $(1-p) \cdot \left(1 - \phi\left(\frac{s-\mu_2}{\sigma_2}\right)\right)$ represents the proportion of individuals who attempt T2 first yet do not recover within s time, and then try T1 and attribute the eventual recovery to T1. Because all individuals eventually attribute their recovery to either T1 or T2, to find the equilibrium expression of the proportion of individuals who attribute their recovery to T1 (hereafter called "T1 individuals"), simply set $p = p_{T1\text{effective}}$ and solve for p (denoted by p^* below):

$$p^* = \frac{1-\phi_2}{2-\phi_1-\phi_2} \quad (3)$$

where $\phi_1 = \phi\left(\frac{s-\mu_1}{\sigma_1}\right)$ and $\phi_2 = \phi\left(\frac{s-\mu_2}{\sigma_2}\right)$. Equation (3) shows that p^* strictly increases with ϕ_1 and decreases with ϕ_2, meaning that the proportion of individuals who think T1 is effective increases with the cumulative density function of the effect timing distribution of T1 and decreases with that of T2. In other words, this analytic result reassures us that there are more T1 individuals at equilibrium when T1 is more effective ($\mu_1 < \mu_2$). To provide some concrete intuitions, I numerically solved for p^* as shown in the Fig. 2, assuming the effect timing distributions of both treatments have the same σ. As expected, the proportion of individuals adopting T1 first at equilibrium always increases with the mean effect timing of the inferior treatment (μ_2), meaning that the longer it takes for T2 to take effect, the higher the T1 proportion at equilibrium is. The reader, however, may note that such change in p^* is very slight (barely visible in the graph) when s and σ is small ($s = 2$, $\sigma = 1$). This is because when individuals are very impatient and the effect of both treatments occurs in a very narrow time window, close to none of the individuals will experience a recovery within their patience threshold for the first attempted treatment and will therefore try the other treatment. As a result, they will attribute the later recovery to the second attempted treatment, and hence the mean timing of recovery does not matter very much. On the other hand, when s is large and σ is small, T1 individuals (those who would attempt T1 first) approach fixation. The reason here is that while the narrow effect timing window of T1 in this case largely falls within individuals' patience threshold, the effect timing window of the inferior treatment variant T2 does not, meaning that many individuals who attempt T1 first would experience recovery within s, while only a small proportion of individuals who attempt T2 first recover within s. Over time, T1's advantage makes it the dominant treatment in the population.

One other transmission possibility is when the probability of a naive individual adopting T1 or T2 to use first depends on their usage frequency in the parental generation. In this case, a naive individual samples a number of models, looks at what treatments these models attempted in the past, and then makes an adoption decision

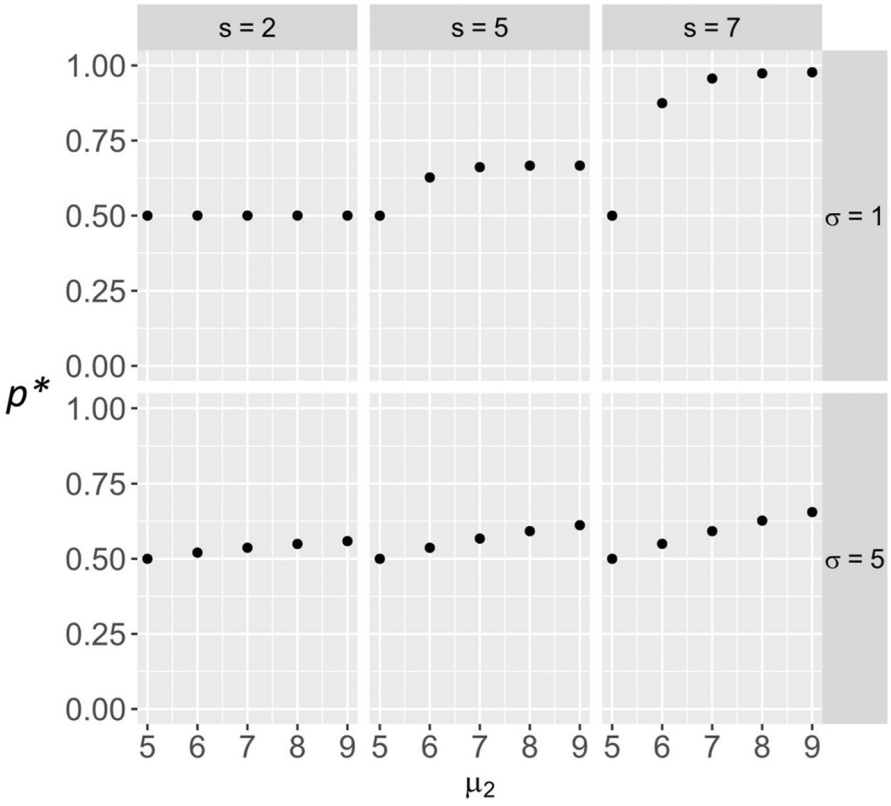

Fig. 2 The equilibrium proportion p^* (proportion of individuals who attribute their recovery to T1) under various parameter combinations when transmission is belief-based copying. μ_1, μ_2, and σ denote the mean and standard deviation of recovery time for T1 and T2 respectively (note both treatments have the same variance). $\mu_1 = 5$ for all conditions. *s* denotes individuals' patience threshold

based on the relative proportion of observed attempts. Conformist transmission, a type of transmission often discussed in the cultural evolution literature, can be thus viewed as a special case of frequency-dependent transmission when the probability of adopting the modal variant is greater than its relative frequency in the population (Henrich & Boyd, 1998). Because in the present setup a model may have up to two actions, this type of transmission will be called action-based copying to avoid terminological confusion, though "conformity" will still be used and will be defined more precisely later.

In my model, with the same notation scheme as above, the total use of T1 in the population is

$$p_{\text{total } T1 \text{ use}} = p + (1-p) \cdot \left(1 - \phi\left(\frac{s-\mu_2}{\sigma_2}\right)\right) \tag{4}$$

where p represents the proportion of individuals who attempt T1 first, and $(1-p) \cdot \left(1 - \phi\left(\frac{s-\mu_2}{\sigma_2}\right)\right)$ represents the proportion of individuals who attempt T2

first, do not observe an effect within s, and then attempt T1. Similarly, the total use of T2 is

$$p_{\text{total } T2 \text{ use}} = (1-p) + p \cdot \left(1 - \phi\left(\frac{s-\mu_1}{\sigma_1}\right)\right) \tag{5}$$

In the next generation, the proportion of individuals who adopt T1 to use first is thus[5]

$$\frac{p_{\text{total } T1 \text{ use}} + D}{p_{\text{total } T1 \text{ use}} + p_{\text{total } T2 \text{ use}}}$$

where D is the conformist bias parameter and is positive when $p_{\text{total } T1 \text{ use}} > \frac{p_{\text{total } T1 \text{ use}} + p_{\text{total } T2 \text{ use}}}{2}$ and negative when $p_{\text{total } T1 \text{ use}} < \frac{p_{\text{total } T1 \text{ use}} + p_{\text{total } T2 \text{ use}}}{2}$. Here, conformist bias increases as the absolute value of D increases. Technically speaking, in order for $\frac{p_{\text{total } T1 \text{use}} + D}{p_{\text{total} T1 \text{use}} + p_{\text{total} T2 \text{use}}}$ to be properly bounded between 0 and 1, D needs to fall within the range $-p_{\text{total } T1 \text{ use}} < D < p_{\text{total } T2 \text{ use}}$. In the following analysis we assume the magnitude of D is small and does not go out of bounds (in a later analysis, transmission with conformity will be explored with an agent-based simulation). To find equilibria, again, set

$$p = \frac{p_{\text{total } T1 \text{ use}} + D}{p_{\text{total } T1 \text{ use}} + p_{\text{total } T2 \text{ use}}} \tag{6}$$

Solving for p (denoted by $p^{*\prime}$), we have two possibilities here. When $\phi_1 = \phi_2$, we have the special case where T1 and T2 are completely identical with regard to their effect timing distribution. Assuming $D > 0$, we have

$$p^{*\prime} \begin{cases} \left|\frac{D+\phi_1-1}{2(1-\phi_1)}\right| & \text{when } p_{\text{ini}} > 0.5 \\ \left|\frac{-D+\phi_1-1}{2(1-\phi_1)}\right| & \text{when } p_{\text{ini}} < 0.5 \\ 0.5 & \text{when } p_{\text{ini}} = 0.5 \end{cases} \tag{7}$$

Because of the existence of biasing parameter D, whose sign depends on the initial population composition, p_{ini} is used to represent the initial (*ini*) population proportion of T1 individuals. In the trivial case of $D = 0$ (no conformist bias), the equilibrium value $p^{*\prime}$ is always 0.5, meaning the percentage of individuals who will attempt T1 or T2 first tends to be the same (50%) in the long run. This makes intuitive sense since, when there are no biasing factors favoring either treatment variant, the long-term equilibrium proportion of individuals who possess either treatment depends on the observed frequency of these treatments being used in the population, which is ultimately determined by their effectiveness (determined by μ and σ).

[5] In the literature, conformity has been modeled in a few different ways. Here I utilize the classic formulation by modeling conformity as an additive constant (Boyd & Richerson, 1985:208; Henrich & Boyd, 1998).

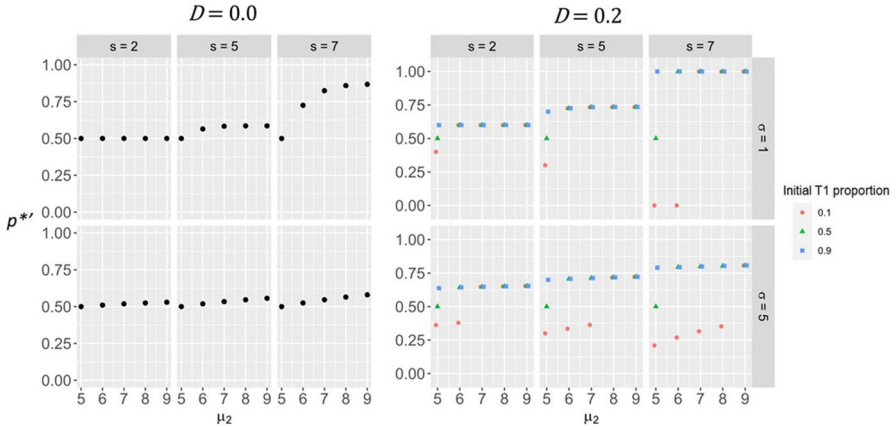

Fig. 3 The equilibrium proportion $p^{*\prime}$ (proportion of individuals who attribute their recovery to T1) under various parameter combinations when the mode of transmission is action-based copying. D denotes the magnitude of conformist bias, μ_1, μ_2, and σ denote the mean and standard deviation of recovery time for T1 and T2 respectively (note both treatments have the same variance). $\mu_1 = 5$ for all conditions. s denotes individuals' patience threshold

When $\phi_1 \neq \phi_2$, solve for $p^{*\prime}$ and we similarly have three solutions (assuming $D > 0$)

$$p^{*\prime} = \begin{cases} \frac{-\phi_2 - \sqrt{D\cdot\phi_1 + D\cdot\phi_2 + \phi_1\cdot\phi_2 - \phi_1 - \phi_2 + 1} + 1}{\phi_1 - \phi_2} & \text{when } p_{\text{ini}} > 0.5 \\ \frac{-\phi_2 - \sqrt{-D\cdot\phi_1 - D\cdot\phi_2 + \phi_1\cdot\phi_2 - \phi_1 - \phi_2 + 1} + 1}{\phi_1 - \phi_2} & \text{when } p_{\text{ini}} < 0.5 \\ 0.5 & \text{when } p_{\text{ini}} = 0.5 \end{cases} \quad (8)$$

As we can see, here $p^{*\prime}$ depends on the initial proportion of individuals who attempt T1 first, p_{ini}, as the value of D changes depending on which treatment is the most common in the population. Note that because $p^{*\prime}$represents a proportion, its sensible values are bounded between 0 and 1 (inclusive).

Again, I numerically solved equilibrium values $p^{*\prime}$ under a few parameter combinations, and the results are shown in Fig. 3. Overall, we observe the same general trend as belief-based copying: the less effective (larger μ_2) the alternative treatment is, the more individuals end up adopting T1 at equilibria states, and this effect is more pronounced when people's patience threshold (s) is large and the spread of the effect timing distribution (σ) is small. Similar to belief-based copying, when individuals are very impatient ($s = 2$), especially when $D = 0$, the equilibrium frequency of T1 barely deviates from 0.5. This is because impatience will increase the chances that an individual tries the alternative treatment regardless of what their first attempt was. Although an individual will attribute recovery to the second attempted treatment, the fact that the individual tried both treatments exactly once means that an observer who focuses on behavior will be equally likely to observe either treatment being used. Again, a small σ means that the timing of recovery is concentrated within a narrow range, and if s is sufficiently close to μ_1, individuals are more

likely to observe the effect of the first treatment and thus will not try the alternative treatment.

When there is conformist bias ($D = 0.2$), the initial frequency of T1 matters, as we observe fixation in the top right panel of Fig. 3, when s is large and σ is small. As discussed above, this particular parameter combination magnifies the difference between superior and inferior treatments, and we see that except in the two conditions where the p_{ini} is small ($p_{ini} = 0.1$) and the efficacy difference of the two treatments is small ($\mu_2 = 5$ and $\mu_2 = 6$, vs. $\mu_1 = 5$), fixation of T1 is always reached. When σ is large, however, individuals who would attempt T1 first and T2 first coexist in substantial proportions. This result contrasts with the standard "one-locus two-allele" cultural evolutionary models in which fixation is guaranteed under conformist transmission (except the unstable equilibrium of ($p_{ini} = 0.5$) (Boyd & Richerson, 1985). In my model, the conformist push toward fixation is countered by individuals' impatience and their trying the alternative treatment when the first treatment does not yield an observable effect within time s.

Agent-Based Model

So far, I have made the rather unrealistic assumption that all individuals in the population are aware of the existence of both treatments and will try one before the other, attempting the second only when the first does not improve outcomes within the patience threshold. This may be applicable to a scenario in which individuals are extremely well-connected with sufficient information flow. Contemporary modern societies, in some respects, have features of this scenario: traditional mass media, such as television and newspapers, can quickly and efficiently disseminates information at little cost, and the growing influence of social media greatly expands our informational network. Thus, one can be aware of the existence of alternative treatments without themselves, their relatives or close friends having any direct experience of it. However, this type of situation is rather novel (Henrich, 2020) and may be quite different from our evolutionary past (Boyette & Hewlett, 2018; Garfield et al., 2016; Henrich & Broesch, 2011; Lew-Levy et al., 2017). Therefore, I construct an agent-based simulation in which agents may not be aware of an alternative treatment to examine the possibility of genuine treatment fixation and extinction.

Brief Model Description

Each agent is represented as a list [T_{first}, T_{second}], where T_{first} denotes the treatment variant that an agent will attempt first, and T_{second} denotes the second treatment variant that the agent has in mind and will attempt if the first attempted treatment does not yield an observable effect within the patience threshold. Note that in addition to the two treatment variants T1 and T2 in the population, T_{second} can also take the value *none*, meaning that the agent is not aware of the existence of the alternative treatment and will not attempt anything even if the first treatment fails to produce an effect within the patience threshold.

Table 1 Notations of parameters used in the analytic model and agent-based simulation

Notation	Meaning
T_{first}	The treatment that the focal individual attempts first
T_{second}	The treatment that the focal individual attempts second if the first attempt treatment fails to yield observable effect in time
T1	Treatment 1
T2	Treatment 2
s	Patience threshold
e	Actual time that it takes for a treatment to come into effect
N	Population size
n	Number of models sampled by the focal naive individual
OA_{T1}	Total observed T1 actions
OA_{T2}	Total observed T2 actions
D	Conformist bias parameter
μ_1, μ_2	Mean of effect timing of T1 and T2
$\sigma_1{}^2, \sigma_2{}^2$	Variance of effect timing of T1 and T2

The initial generation consists of N agents, and each agent performs an action T_{first} and obtains an effect timing e, which follows the effect timing distribution of either T1 or T2 with the respective mean and variance parameters. If $e < s$ (meaning the effect occurred within its patience threshold), the agent will not perform further actions and will attribute the effect to its T_{first}; otherwise it would attempt its T_{second} (if it is not *none*) and attribute the eventual recovery to its T_{second}. If its T_{second} is *none*, then it would not attempt anything and would attribute its eventual recovery to its T_{first} instead. Note that this means when an individual's T_{second} is *none*, it will always attribute its recovery to its T_{first} regardless of whether this recovery occurred within its patience threshold.

The next generation consists of the same number (N) of naive agents, and each naive agent samples and learns from n cultural models in the parental generation (see Table 1 for the meaning of all parameters used in the model). In the case of belief-based copying, there are three possibilities regarding an agent's model composition (causal attributions of the n models) and four possible treatment adoption types:

1. for all T1 attributions and no T2 attributions: the agent will be of the type [T1, none].
2. for all T2 attributions but no T1 attributions: the agent will be of the type [T2, none].
3. for both T1 and T2 attributions: the agent will be of the type [T1, T2] or [T2, T1], with probability relative to the proportion of the T1 and T2 attributions in the sampled models. For example, if there are 4 T1 attributions and 6 T2 attributions, the agent will be [T1, T2] with probability 0.4 and [T2, T1] with probability 0.6.

In the case of action-based copying, treatment adoption works similarly to the above possibilities, with the difference being that the n cultural models are not agents from the previous generation but rather "actions" observed in the previous generation. That is, agents learn from the observed attempts of trying T1 or T2 instead of from only the treatments to which the sampled models eventually attribute recovery. So, unlike belief-based copying, for which each model can only pass down one treatment, for action-based copying, each model can pass down one or two actions, depending on the number of treatments they attempt. The conformist bias factor in the agent-based simulation contributes to the treatment adoption decision in the following way: if we denote the total number of observed actions of T1 and T2 as OA_{T1} and OA_{T2}, respectively, and assume $D > 0$ (note that D here modifies the treatment adoption probability of the individual rather than the treatment frequencies in the population), we have

$$Pr(T1 \text{ adopted}) = \begin{cases} \frac{OA_{T1}+D}{OA_{T1}+OA_{T2}} & |\text{when } OA_{T1} > OA_{T2} \\ \frac{OA_{T1}-D}{OA_{T1}+OA_{T2}} & |\text{when } OA_{T1} < OA_{T2} \\ \frac{OA_{T1}}{OA_{T1}+OA_{T2}} & |\text{when } OA_{T1} = OA_{T2} \end{cases}$$

After all naive agents' types are determined, they become the parental generation and the cycle continues. To ensure convergence, all simulations are run until the calculated equilibrium frequency of different types of agents does not fluctuate past 0.1% for 10 consecutive generations. In all simulation runs, the initial population consists of equal proportion (50% each) of [T1, T2] [T2, T1] individuals. This initial setup gives both treatments the best chance to spread (all agents have both treatments in mind) and thus allows us to examine the possibility of treatment fixation and extinction fully.

Results for Belief-Based Copying

The simulation results of belief-based copying are shown in Fig. 4. Immediately, we see that the magnitude of s plays a significant role in the equilibrium frequencies of different types of individuals. Specifically, when s is small (i.e., when agents are so impatient relative to the mean effect times that the timing of recovery does not matter),[6] the relative frequencies of agent types do not change with the increasing difference between μ_1 and μ_2. When the number of sampled models (n) is small ($n = 3$), random sampling (drift) causes a substantial proportion of individuals to only experience one treatment variant. As we see in the case of $s = 2$, roughly a quarter of the

[6] Throughout the paper, s is assumed to be fixed (i.e., all individuals in the population have the same patience threshold). A potentially interesting scenario to examine is what happens when s is allowed to vary among individuals and has a large variance. Presumably, a large variance in s means there will be a mix of very patient and impatient individuals, and the most impatient ones may still prevent the fixation of the more effective (fast-acting) treatment. Future work may examine such dynamics more directly.

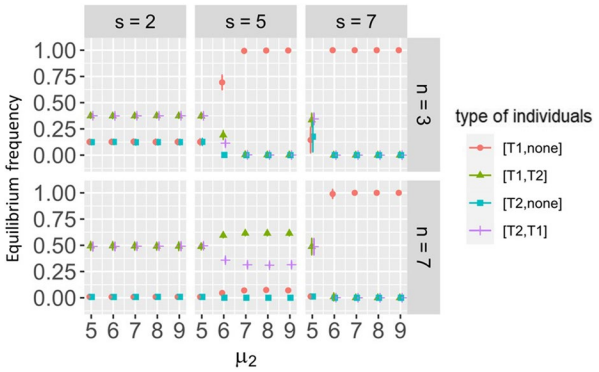

Fig. 4 Equilibrium frequencies of different types of individuals under belief-based copying. Error bars represent 95% confidence interval from 200 independent simulation runs. μ_1, μ_2 and σ^2 denote the mean and variance of recovery time for T1 and T2, respectively (note both treatments have the same variance), and s denotes individuals' patience threshold. Other parameter values: $\sigma_1 = \sigma_2 = 1$, $N = 500$, $\mu_1 = 5$ for all conditions

population are not aware of the existence of an alternative treatment, and as a result all four types of agents stably coexist in the population. When n is reasonably large ($n = 7$), on the other hand, there is roughly a 50–50 split between [T1, T2] and [T2, T1] types of individuals.

Corroborating previous analytic results, Fig. 4 shows that a large s leads to fixation of the superior treatment variant rather easily. In the case of $s = 7$, for example, when T1 is only slightly better than T2 ($\mu_1 = 5$ compared with $\mu_2 = 6$), [T1, none] reaches fixation when $n = 3$ and near fixation when $n = 7$. When s is of intermediate magnitude and n is large ($s = 5$, $n = 7$), we see the stable coexistence of three types of agents (ordered by their equilibrium proportion in the population): [T1,T2], [T2,T1], and [T1, none], suggesting that although agents who would attempt either T1 or T2 first while entertaining the possibility of the other treatment exist in the population, a small proportion of individuals ([T1, none]) is no longer aware of inferior treatment T2, and this proportion increases with the increasing difference in the mean recovery time of the two treatments up to a point. In the $s = 5$, $n = 7$ condition, for example, the frequency of [T1, none] barely changes above $\mu_2 = 7$; correspondingly, [T2, T1] individuals decrease up to the same point. This means that at a particular patience threshold the disadvantage of the inferior treatment in the transmission process has an upper limit: in the above parameter combination ($s = 5$, $n = 7$, $\mu_1 = 5$), whether the alternative treatment takes an average of 7 time units or 9 time units to take effect does not matter—in either case the inferior treatment will exist in the population at the same low frequency.

Results for Action-Based Copying

The simulation results of action-based copying are shown in Fig. 5. There are a few points worth noting here. First, action-based copying with no conformity ($D = 0$) leads to no fixation of treatment variants under the current parameter

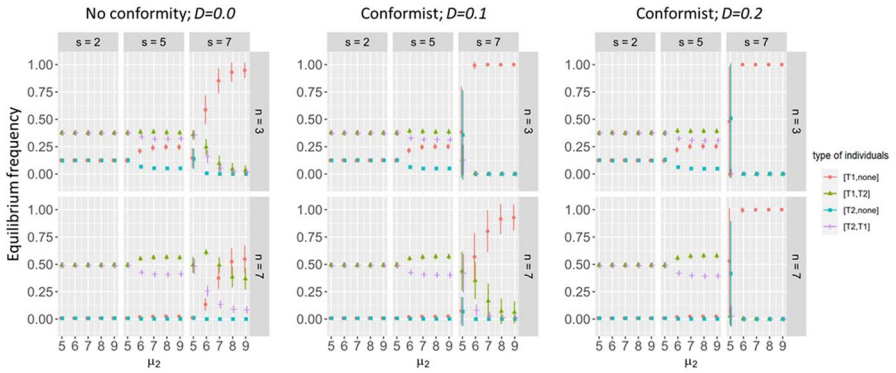

Fig. 5 Equilibrium frequencies of different types of individuals under belief-based copying. Error bars represent 95% confidence interval from 200 independent simulation runs. D denotes the magnitude of conformist bias, μ_1, μ_2 denote the mean recovery time for T1 and T2, respectively (note both treatments have the same variance), and *s* denotes individuals' patience threshold. Other parameter values: $\sigma_1 = \sigma_2 = 1$, $N = 500$, $\mu_1 = 5$ for all conditions

settings, though one may expect [T1, none] to reach near fixation when μ_2 gets sufficiently large in the condition of $s = 7$, $n = 3$. In the classic cultural evolution literature, unbiased frequency-dependent transmission does not change the relative frequency of cultural variants under certain conditions (e.g., infinite population size; Boyd & Richerson, 1985), similar to the Hardy-Weinberg equilibrium in population genetics (Meirmans, 2018). Our model is different, however, in that the units are not agents but rather actions in the previous generation since one agent can potentially have two actions, and whether the second treatment is used depends on the effect timing of the first treatment. Therefore, equilibrium values of different types of agents are uniquely determined by the effect timing distribution parameters μ, σ, and the agent's patience parameter *s*, as well as number of sampled actions *n*. Regarding fixation of the superior treatment variant (T1), as long as some T1 attempts are not followed by timely recovery, T2 actions will exist in the population that will be sampled by the naive generation. In our model setup, one alternative treatment action sampled is sufficient for the agent to be aware of its existence, which is why an increased number of sampled actions *n* greatly increases the equilibrium proportion of [T2, T1] agents.

Action-based copying with conformity, on the other hand, does lead to genuine fixation when the patience threshold is large ($s = 7$), especially in cases where *n* is small. Because the initial population composition is set to be of equal proportion of [T1, T2] and [T2, T1] individuals, all fixations occur with [T1, none] reaching 100% in the population. That is, no agent in the population is aware of the existence of T2 anymore and thus will not attempt it even if T1 doesn't yield observable effect within *s*. The magnitude of *D* primarily matters when there are more model actions sampled; not surprisingly, a larger *D* makes fixation more likely. In fact, when T1 and T2 are identical regarding their effect distribution ($\mu_1 = \mu_2 = 5$), the population reaches fixation either in the form of [T1, none] or [T2, none] with roughly equal chance, which is why we observe rather large error bars.

The fixation pattern under action-based copying with conformity for other parameter values is qualitatively similar to that under belief-based copying, though its parameter requirement is more stringent: for example, we observe no fixation under the intermediate patience threshold value ($s = 5$). This suggests that the magnitude of s matters more when the superior treatment variant reaches fixation due to conformity. When the patience threshold s is not sufficiently large, a significant proportion of individuals will attempt both treatments due to impatience, which sustains substantial amount of both T1 and T2 in the pool of actions. As can be seen in Fig. 5, in conditions of $s = 5$, the relative proportion of different types of individuals does not change much with D or μ_2, indicating that the patience threshold s (relative to the magnitude of μ_1 and μ_2) is the real limiting factor here.

Discussion

In this paper, I pose the puzzle of ineffective medical treatments and formally model a hitherto ignored aspect of technological practice in the cultural evolution literature: when a problem has multiple potential solutions and people are aware of them, they rarely stick to one solution blindly. Rather, people readily turn to alternative solutions when one solution fails to solve a problem. This aspect of psychology interacts with the fact that many medical treatments do not yield immediate, observable outcomes, and hence, it is difficult to distinguish an ineffective treatment from a slow-acting one. The result is that people try one treatment after another. Such sequential applications of different treatments present unique challenges to adaptive cultural evolution since inferior medical treatments may stably coexist with superior treatments due to erroneous causal attribution based on temporal contiguity. In a sense, inferior (slower-acting) treatments can "hitchhike" (for a general introduction to the concept of hitchhiking in evolutionary biology, see Barton, 2000) upon the therapeutic effect of superior (faster-acting) treatments. This may hold true for ineffective treatments as well.

How Does the Inferior/Slower-Acting Treatment Persist?

If we take the superior treatment variant to be a genuinely effective medical treatment and the inferior treatment variant to be an ineffective treatment where the probability of recovery is no different from chance, then my model describes an important factor that contributes to the persistence of ineffective treatments: the natural variation in the timing of recovery and individuals' limited patience make a proportion of the population turn to the ineffective treatment, and these individuals then attribute their eventual recovery to the temporally closer but ineffective treatment, rather than the genuinely effective treatment. Anthropologically, although the published literature usually focuses on healing practices with explicit supernatural components (thus the puzzle of "ineffective treatments"), the reality is that more naturalistic treatments such as herbal remedies which likely have real therapeutic effects often coexist with supernatural, ineffective treatments (Montagu, 1946; Murdock

et al., 1980; Pan et al., 2014). In fact, much effort has been devoted to scientifically validating the genuine therapeutic effect of traditional medical practices (Firenzuoli & Gori, 2007; Saad et al., 2006; Taylor et al., 2001; Yuan et al., 2016). Most notably, the 2015 Nobel Prize in physiology or medicine was awarded to Tu Youyou for her discovery of an effective malaria treatment, artemisinin, which was recovered from an ancient medicine recipe book by alchemist/healer Ge Hong (283–343 CE) during the Jin Dynasty (Miller & Su, 2011).

Previously, Tanaka et al. (2009) modeled a social dynamic in which ineffective medical treatments may spread because their ineffectiveness results in longer and more salient demonstrations than effective treatments. My model here thus complements this line of research which focuses on the information transmission dynamics that contribute to the persistence of ineffective treatments. The relative importance of this factor will surely depend on cultural context; as I have already alluded to, societies with sufficient information flow, such as ours, are, paradoxically, particularly vulnerable to the inferential problem presented by sequential treatment. Yet, modern societies have reliable epistemic institutions (research agencies, universities, etc.) that generate genuine knowledge using scientifically valid methods (e.g., randomized controlled trials; Hong & Henrich, 2021). I suggest that the sequential treatment factor probably plays a larger role in many small-scale societies that are increasingly influenced by the spread of modern medical theories and the availability of modern medical facilities: on the one hand, the actual therapeutic efficacy of modern medical practices in these places may not be very high because doctors may be poorly trained (misdiagnosis can happen); on the other hand, modern medical treatments are often viewed as alien and, when accompanied by colonialism, generally trigger some level of suspicion and distrust (Abdullahi, 2011). Since traditional medicine often works through placebo, and distrust in modern medicine minimizes the placebo effects of modern medicine, it is possible that even if modern medicine is on average more effective, the placebo effects of traditional medicine may minimize that difference to the point of being imperceptible. The implication is that we should not expect that people will automatically give up their traditional healing practices and wholeheartedly endorse modern medical ones, even if they exclusively focus on therapeutic outcomes.

When Does the Superior/Faster-Acting Treatment Evolve to Fixation?

The logic of natural selection dictates that the frequency of the variant with higher fitness will increase in the population. In genetics, we can precisely calculate the probability of fixation under various conditions (Hartl & Clark, 1997), but the general expectation is that the variant with higher fitness will reach fixation in the long run if we consider natural selection as the main evolutionary force. Cultural evolutionary theory, on the other hand, also generally expects the variant that confers higher fitness benefits to increase in frequency, and it does so via a number of transmission mechanisms that are quite different from genetic ones (Boyd & Richerson, 1985; Henrich, 2016). Conformist transmission, for example, can often lead to fixation of the more common cultural variant, and when it is combined with other

evolutionary forces that favor the variant with higher fitness (Henrich & Boyd, 1998; Nakahashi et al., 2012, Hong, 2022b), adaptive evolution will occur in the form of the variant with higher fitness reaching fixation.

My model, however, shows that when additional constraints and psychological realism (i.e., individuals are able to mentally entertain multiple treatments) are included, it may be more difficult for the superior treatment to reach fixation. Under both belief-based and action-based based copying, some minimal level of patience is needed for the inferior treatment variant to be driven into extinction. Specifically, it takes time for different treatment variants to reveal their effect, and when people are too impatient, superior treatments cannot sufficiently distinguish themselves from inferior ones. Another important factor that affects the possibility of adaptive fixation is the number of models sampled. Intuitively, if individuals sample a very large number of cultural models, they are more likely to experience alternative treatment variants and retain these variants in their mind. This makes fixation more difficult—because regardless of the patience threshold level, there are always going to be individuals who wait long enough without observing an effect and are willing to try an alternative *if they have an alternative in mind*. Sampling a large number of cultural models ensures that individuals in the population are aware of the existence of alternative treatments.

Of course, genuine treatment fixation does happen. As discussed above, a small number of sampled models and a large patience threshold increases the chances that a superior treatment reaches fixation. My model shows that everything being equal, fixation of the superior variant occurs more easily under belief-based copying than action-based copying. It should be reiterated that these transmission mechanisms are defined in rather specific ways in the sequential treatment context and should not be confused with payoff-biased transmission and frequency-dependent transmission in the cultural evolution literature despite their resemblance. The transmission of cultural variant can be modeled in many other ways; for example, individuals could track the time between the application of some treatment variant and the recovery of others and preferentially adopt the treatment with shorter recovery delay, or they could differentiate whether the observed action is the first or second attempt and assign more weight to the first attempted action (in the current model all actions have the same weight). We could even add more sophistication and allow individuals to perform some kind of Bayesian inference by taking into account the existence of a patience threshold and/or the number of cultural models sampled. These possibilities merit further theoretical and empirical investigation, but the general point remains that as long as people have a tendency to favor treatments that occur temporally closer to recovery, the complete elimination of the inferior treatment variant may be difficult to achieve.

Conclusion

The application of knowledge is very different from the discovery of knowledge. In everyday life, people frequently encounter situations with great uncertainty and need to make decisions based on incomplete information. In the context of

problem-solving, an individual's immediate concern is to resolve the problem using whatever means necessary without being too concerned about whether these instrumental means are genuinely effective. Although it has been argued that even children exhibit some level of scientific thinking (Gopnik et al., 2001; Koslowski, 1996; Sodian et al., 1991), much developmental work has shown that children's use of experimentation to test a hypothesis is often driven by an "engineering approach" to create desirable effects rather than to correctly identify cause and effect (Kuhn & Phelps, 1982; Schauble, 1990; Schauble et al., 1991; Tschirgi, 1980). Relatedly, my own fieldwork among the Nuosu in southwest China shows that many people readily acknowledge that they are not certain about whether their illness is caused by ghosts/spirits, imbalance of bodily elements (*yin-yang*), or germs/viruses, yet to ensure a speedy recovery they are willing to "cover all the bases" and employ multiple types of treatments either sequentially or simultaneously. In the most extreme case, a traditional healing ritual (on the basis that illness is caused by a spirit) may be performed inside a hospital as the patient receives modern medical treatment (Hong, 2022b). Note that this is not the ideal way to discover which treatment works better—a modern statistician is likely to require a large quantity of data and perform sophisticated analyses (sometimes referred to as "sequential causal inference" in the literature; see Wang & Yin, 2015) to make reasonable inferences.

Granted, people do possess some degree of curiosity and are capable of performing some level of primitive hypothesis testing through active experimentation. Medical treatments, however, are uniquely challenging for experimentation for two related reasons. First, performing a medical experiment in the modern sense can be not only costly but also morally unacceptable because of the high stakes involved (sometimes being a matter of life or death). Any sort of treatment vs. control experiment would mean that some individuals are not receiving the best medical care given the present state of medical knowledge (Nardini, 2014). Although the epistemic merits conferred by randomized, controlled trials (RCTs) are highly valued in contemporary, modern societies, RCTs in the modern sense only occurred within the past two centuries (Stolberg et al., 2004), and there is no reason to think that they were similarly valued in small-scale or historical societies. Second, in the case of medical treatments it may be challenging to create the "experimental setup." Testing whether some treatment works on some illness requires generating or identifying individuals with the illness, which can be very difficult if not practically impossible, especially when its causal mechanisms are not understood and/or the illness occurs rarely. In this sense, testing whether certain medical treatments cure some illness is rather different from exploring which projectile point design is more effective at bringing down prey. As such, "medical experimentation" is typically problematic and therefore not done in traditional societies.

From an evolutionary perspective, natural selection shaped the human mind to solve various kinds of adaptive problems (Cosmides et al., 1995). As such, our motivation and capability of obtaining truth would only be selected insofar as they confer fitness benefits. Therefore, "truth for truth's sake" may not be a fundamental aspect of human nature (Mercier & Sperber, 2017), especially when seeking truth involves a cost. In the medical setting, it would be rather silly to avoid a potential life-saving treatment simply because doing so makes causal inference easier. Relatedly, this is

also why the idea of a "control group" does not quite make sense when the primary goal is to maximize the chance of recovery. Instead of active experimentation by the individuals themselves, adaptive cultural evolution is more likely to occur through social learning wherein individuals observe and learn from those who appear more successful or prestigious (Henrich & McElreath, 2003), a process that is more prone to errors, biases, and occasional maladaptive cultural practices (Richerson & Boyd, 2005).

The combination of evolved psychology and cultural dynamics has important consequences for our culturally evolved solutions to medical problems. For one thing, my model suggests illnesses that appear serious enough yet may spontaneously recover within relatively short periods of time present a special inferential problem for weeding out treatments that do not affect the timing of natural recovery. The symptoms of a common cold, for example, typically last for a few days before spontaneous recovery, with few effective treatment options (Wat, 2004). Yet there exist many alternative and complementary treatments in the market (Nahas & Balla, 2011). Relatedly, genuinely effective yet slow-acting drugs may sometimes fail to be recognized, as in the case of osteoarthritis (Bruyère et al., 2008; Gumustas et al., 2017).[7] My model also indicates that when one treatment is significantly superior to alternatives in speeding up recovery, it is nonetheless likely to reach fixation, especially with the help of conformity. The rapid acceptance of Western medicine in treating eye-related diseases by the Chinese in southern China in the late nineteenth century nicely illustrates this point: Western doctors' surgical treatments yielded almost immediate effects and quickly outcompeted traditional Chinese alternatives (Hao & Zhu, 2010).

It is worth reiterating that although my model resembles the information transmission dynamics of contemporary social media in some aspects, it most aptly applies to small-scale societies with decentralized information flow. Unlike in contemporary societies, where there are centrally organized epistemic institutions, individuals in small-scale societies typically rely on a combination of personal experience, testimonial information, and observations of others' actions. As a result, the beliefs and technologies they adopt are subject to a different set of biases (Hong & Henrich, 2021). In modern societies with competent and reliable epistemic institutions, more effective medical treatments can more easily disseminate in the population through lay people's trust of medical experts and authorities.

To summarize, in this paper I used a formal modeling approach to explore the phenomenon of sequential medical treatments in which individuals entertain multiple alternative treatments, trying one first and then attempting another when the first treatment fails to produce observable outcomes within a certain period of time. My results show that although fixation of the superior/faster-acting variant does happen, treatments with different recovery times can coexist under two different transmission rules and a wide range of parameter combinations.

[7] My fieldwork among the Nuosu suggests that many people believe that it's of no use to go to the hospital if one has osteoarthritis (风湿).

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Code Availability Agent-based simulation is conducted in python 3.8. All analytic and simulation codes as well as data generated are available at https://github.com/kevintoy/sequential_medical_treatment.

Declarations

Conflict of Interest None.

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