Social Search Evolves with the Emergence of Clustered Environments

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Abstract

Social search (using social information to locate resources) has evolved stably across a wide range of species. The current research systematically investigates dynamical interactions between social search strategies of consumers and clustering of resource environments in simple 2D worlds. Previous work finds that clustering of resources (e.g., information, food) promotes use of social search, and other studies find the corresponding effect that social search leads to increased resource clustering. In Experiment 1 and 2 we replicate these results in simulations by fixing resource distributions and social search respectively at different levels and observing their influence on the other. Our results additionally show an inverse U-shaped trend between the two— as resource clustering increases, so does social search (as expected); however, at very high values of clustering, adaptive benefits of social search decline. Similar trends are obtained when social search is manipulated and resulting resource clustering is analyzed. In Experiment 3, we simulate dynamical systems where both social search and resource clustering are left unconstrained so they can mutually influence one other. These simulations are representative of real-world systems where species can flexibly alter their search strategies in response to the environment (e.g., through learning or evolution) and resource distributions are in turn influenced by consumer behavior. Here, we find that both social search and resource clustering evolve to positive values, indicating that they may be stable states of such systems. Our results have implications across a wide range of search domains—similar dynamics between social search and resource clustering are observed in multidimensional environments of informational and cultural search and simpler 2- and 3-D environments of ecological search.

Introduction

Using social information to search for resources—henceforth referred to as social search—has stably evolved across a wide range of species. For instance, birds indicate locations of fertile patches through vocal communication, fish search for food in schools, ants produce and follow pheromone stigmergic trails, and humans “follow” other humans on social media in search for information. Even such simple social engagement can provide large adaptive benefit in locating resources (food, mates, information etc.)—it allows agents to expand their search radii by piggybacking on the search radii of other agents. For instance, researchers have repeatedly cited the improved abilities of finding food produced by a larger number of searching eyes as an evolutionary explanation for flocking and schooling behaviors (Pitcher, Magurran, & Winfield, 1982).

Studies have frequently explored conditions that encourage evolution of social search strategies. A common finding is that social search evolves more readily when resources are highly clustered or patchy. For instance, Wu et al. (2021) found that human participants in a Minecraft game were more likely to engage in social observation and imitation (by following other participants) when resources were distributed in clumps than when they were randomly dispersed. Brown and Orians (1970) also indicate that across species, flocking evolves when the primary resource is patchy, while territoriality is more common under random dispersal. This effect is intuitive—a high density of foragers is indicative of a fertile patch. Further, when resources come in clumps, larger numbers of individuals can consume them simultaneously, producing a benefit for following a potentially successful forager who may find a new clump. On the other hand, when resources are randomly distributed, there is less likely to be enough resources in a given local area for sharing to be possible, reducing the benefit of following other foragers.

Similar logic can be applied to inextinguishable resources like information on the internet—social search is highly adaptive here because the value of information does not often reduce much (if at all) when “consumed” by others and therefore it can be shared. Resources, across domains, often come distributed in clumps—for instance, food resources like vegetation and prey are patchy and informational resources like website pages are clustered (Adamic, 1999; Levin, 1992). This explains the ubiquity of social search—it is adaptive in the clustered environments frequently faced by humans and other animals.

Research has also focused on the corresponding effect of social search on resource distributions, finding that it can lead to increased resource clustering. For instance, phytoplankton patchiness is sometimes attributed to the schooling of foraging krill (Whitehouse et al., 2009). Further, preferentiality for socially popular nodes is potentially the cause of high clustering in social networks (Barabási & Albert, 1999). A possible explanation for such an effect is that social search leads to attraction toward already popular resource locations, leading to their overconsumption. This produces regions of overexploited resources, while other regions are left underexploited, leading to an overall patchy structure. For instance, Donaldson-Matasci and Dornhaus (2014) found that bee communities with effective dance communication were
more likely to consistently exploit popular nectar patches while those with impaired pollen communication were more like to explore and find rare pollen types.

Thus, social search and resource patchiness may mutually interact, with each encouraging the development of the other. Here we study this relationship in simulated 2D worlds where autonomous agents, resembling animals, search for and consume “growing” resources, resembling plants. In some simulations, agents can evolve social strategies that are adaptive in the particular resource distributions. We equip our agents with a basic social search ability—movement toward other searching agents—which has also been demonstrated by evolutionarily early organisms like bacteria (Park et al., 2003). In turn, we also run simulations to study the influence of search strategies on resource clustering—here, resource distributions emerge from the consumption patterns of collectively searching agents. In previous work, we found that simpler non-social search strategies produced clustering of resources (Luthra, Izquierdo, & Todd, 2020); here, we seek to determine if social search increases such resource clustering and vice versa.

Therefore, we run three experiments—(1) clustering of resources is held fixed at different levels and its effect on social search is observed, (2) social search is held fixed at different levels and its effect on resource clustering is observed, and (3) neither are held fixed, allowing for both to influence one another continuously in a dynamical fashion. This third experiment enables us to observe the trajectories and stable states of search strategies and resource distributions in a dynamical model. While both the effect of search behavior on clustering and the effect of clustering on search behavior have been previously explored, the mutual interaction of the two forces has been challenging to study—this third experiment adds to existing literature by investigating such dynamics.

**Model**

Consumer agents move in a continuous 100×100 2D world. Each agent accrues energy units that represents its success in the world. On every timestep, agents perform some basic behaviors that regulate their energy units and sustain evolution. These include (1) consuming 10 energy units of resources if available in a 0.5-unit radius, (2) moving to a different location in search of food, selected through computational calculations representing their search strategy (described below), (3) metabolizing 5 energy units (occurring compulsorily, regardless of movement), and (4) reproducing asexually if total accumulated energy units cross 20. When reproduction occurs, the offspring is given half the energy units of the parent and it takes position at a random distance chosen from an exponential distribution (decay rate 0.3). In simulations where search strategy is a dependent variable and evolves in response to the environment, the offspring inherits the parent’s search strategy with random mutation. Agents die if their energy units fall below 0, which occurs if they are unable to consume resources for several timesteps since they are continually metabolizing and losing energy. Hence, an agent’s ability to find resources determines their evolutionary success—they are less likely to die and more likely to reproduce. Initially, 50 consumer agents and 2000 resources are introduced in the world—both reproduce and increase in numbers, eventually stabilizing with some oscillations that resemble Lotka-Volterra dynamics.

**Search Strategy**

Agents must move in directions of high resource concentrations to best survive and reproduce. Each agent has a constant step size, chosen from a normal distribution (mean 1, SD 0.1) and on every timestep an agent moves one step. To make optimal movement decisions, agents are equipped with basic smell-like perception—resources and other consumers

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**Figure 1:** (A) A snapshot of the world from a random simulation displaying resources in green and consumers in white. (B) The corresponding distribution of resource and consumer odors across the world. The weight for resource odors is fixed at 1 for all simulations, while weight for consumer odors \( \alpha \) evolves in the populations depending on fitness (in Experiment 1 and 3) or is held fixed at varied values to determine influence on resource distribution (in Experiment 2). In the displayed figure, \( \alpha \) is fixed at 1. (C) Agent movement demonstrated by zooming into a small section of the odor landscape. The white dot is an agent that must choose the most attractive location for its next step. Potential options are displayed as black dots (the agent’s step size determines the radius). The final decision is marked by the red cross, chosen using a softmax function on the attractiveness of the potential spots.
produce normally distributed odors (mean 0, SD 1.5) and agents can perceive these odors and make movement decisions that take them toward or away from the source. Each agent is equipped with odor weight parameters, ranging from -1 to +1, that determine how they value each source of odors—positive weights indicate attraction and negative weights indicate repulsion to the source. Therefore, agents “sniff” in all directions (at a radius determined by their step size), through a softmax function they probabilistically choose a direction perceived as attractive, and finally they take a step in that direction at their step size. The functioning of this movement model is displayed in Figure 1.

Agents can distinguish between resource odors and consumer odors; however, they cannot ascribe individual identity to resources or other consumers. Therefore, in our initial simulations, we let agents evolve two odor weight parameters—one for resources and the other for consumers. Unsurprisingly, agents then always evolved extremely high weight parameters for resource odors since evolutionary pressures create high motivation for resource attraction. To simplify the model, we fixed the weight for resource odors at +1 and only allowed the consumer odor weights to evolve. This weight determines the extent to which agents use social information—that is, the location of other consumer agents—as indications of resource concentrations. High values of this social search parameter will produce social foraging strategies, with agents following other consumers and searching in mini-flocks; values close to 0 will produce individualistic foraging where agents are indifferent to other agents; finally, negative values will produce competitive foraging, with agents actively moving away from other agents. Figure 2 distinguishes between the different search strategies by displaying instances of each.

In Experiments 1 and 3, the social search parameter (consumer odor weight) is evolved in response to the environment. Here, agents pass the social search parameter to their offspring with an added mutation chosen from a normal distribution (mean 0, SD 0.025). The social search strategy that is most successful eventually dominates the population and we analyze the distribution of the evolved parameters. In contrast, in Experiment 2 social search is an independent variable whose effect on resource distribution is studied. Hence in that case, particular values of the social search parameter are held constant throughout each simulation.

**Resource Distribution**

The resources consumed by agents have similar reproduction parameters as agents—on every step, they consume some invisible uniformly distributed resource (akin to sunlight), metabolize, and reproduce when their energy units cross a threshold of 20 units. However, unlike consumers, they are immobile and do not change location from where they are first “rooted” (locations of offspring positions differ across experiments as described in further detail below). Further, like real-world ecological resources, they lose energy when consumed by agents and disappear if their energy falls to 0. To avoid overcrowding of resources in any location, we assume that each resource occupies 0.2 radius—two resources cannot simultaneously grow within this radius.

In Experiment 1, resource distribution is an independent variable and is therefore fixed at various levels to artificially create environments varying in patchiness. Here, we pick 20 random locations in the world and 100 resources grow at a random dispersal distance from each location. The dispersal distance is chosen from an exponential distribution with decay rate depending on the cluster condition of the simulation. Therefore, a low decay rate produces high cluster environments where resources grow in patches and high decay rates produce random distributions. Figure 3 displays resource distributions with various decay rates. When a resource reproduces, new offspring take position within the same patch at a similarly chosen distance from the original “seed” location. As with real-world resource patches which vary in

![Figure 2: Demonstration of social search values. Consumers, resources, and empty space are represented by white, green, and blue colors respectively. Positive social search produces attraction (so consumers form groups), negative produces repulsion (so consumers disperse), and the magnitude indicates intensity.](image-url)

![Figure 3: Clustering environments produced by varying the decay rate (DR) of the exponential dispersal distance. We also display the clustering measurement (CM) corresponding to these environments—as can be seen, it shares an inverse relationship with the decay rate. The displayed clustering environments were used as the different conditions of Experiment 1. In Experiments 2 and 3 the resource structure that emerges over time is measured by the same cluster measure demonstrated here.](image-url)
fertility across time, in these simulations the locations of fertile patches change—after every 40 steps, a previously fertile patch location (chosen randomly) stops growing and a new patch location is selected at a random position and 100 resources are introduced at this patch (using the same processes described above). This creates constant evolutionary pressure for the agents to find fertile patches.

In Experiments 2 and 3, distribution of resources is a dependent variable, influenced by the consumption dynamics of agents. In these simulations, we do not fix resource distributions to particular locations, as described above. Instead, resources can “grow” anywhere across the world. Initially, 2000 resources are introduced in random locations; new resource offspring take position close to the parent at a distance chosen from an exponential distribution (decay rate 0.3, similar to consumers)—hence, they spread outward (akin to foliage). Since resource locations are not fixed to grow in pre-specified patches, the resource distribution that emerges in the world is dependent entirely on how they are consumed by the agents based on their search strategy. We can measure the resulting resource clustering based on the Clark and Evans (1954) nearest neighbor coefficient. This is the average distance between a resource and its nearest neighboring resource divided by an estimate of what the average distance would be under a random Poisson distribution. We use Thompson's (1956) variation of the metric, measuring patchiness based on the 3rd nearest neighbor (instead of the closest neighbor) because it is less susceptible to noise. We subtract this ratio from 1 to produce our clustering measure, which is equal to 0 if resources are randomly distributed, above 0 if they are clumped, and less than 0 if they are overdispersed. The clustering metric has an inverse relationship with the exponential decay rate, as shown in Figure 3. It is calculated as follows:

\[
M_3 = \frac{\text{mean dist. to } 3^{rd} \text{ nearest neighbor}}{E_3}
\]

\[
E_3 = \frac{\text{expected dist. to } 3^{rd} \text{ nearest neighbor}}{\sqrt{\text{density}}}
\]

The clustering metric used here uses a similar approach to the clustering coefficient popularly used in network science (Watts & Strogatz, 1998), applied to nearby points in space rather than connected nodes in a network.

**Experiment 1: Fixed Resource Clustering**

In this experiment, we manipulate resource distribution and measure the search strategy that evolves in response to the resource environment. We varied resource distribution as described above in seven conditions (displayed in Figure 3) and measured the resulting level of social search by averaging agents’ social search weight—that is, the evolved attraction they have to odors of other consumers (demonstrated in Figure 2). As stated earlier, we expect that as patchiness increases, tendencies for social search will also increase.

We ran ten simulations of each of the seven resource distribution conditions. Each simulation was run for 1000 timesteps.

**Results and Discussion**

Figure 4A displays the distribution of social weights in the last 200 steps of the simulations. As can be seen, there is generally an upward trend in social search resulting from increases in resource clustering—in the lowest clustering condition (that is, under random dispersal), agents display an...
average social search of -0.2 (indicating repulsion from other consumers) and in cluster environment 6, agents display an average social search of +0.26 (indicating attraction toward other consumers). These results are as expected—in clumpy environments in the real world, an accumulation of foragers is often indicative of fertile locations, and due to the high density of resources in those fertile locations sharing of the resources is possible, encouraging the evolution of social search among animals. Although the overall trend is positive, we interestingly find that in the highest clustering condition (environment 7), social weights are lower than that of the two lower clustering conditions (i.e., environments 5 and 6). This difference is significant at p<.05. We therefore obtain an almost upside-down U-shaped trend.

To understand these results better, we took a closer look at the environments for the various clustering conditions (displayed in Figure 3). As can be seen, in the highest clustering condition, resources are distributed in extremely delineated and disjointed patches. On the other hand, in clustering environments 5 and 6, the patches are more noisy with fuzzier boundaries. Social search may be more beneficial in noisier patch environments where agents are more susceptible to sampling errors produced by their limited sensing abilities—that is, they may be more often misled by small-scale resource fluctuations produced by noise to mistakenly think a good patch is in a particular direction, or to miss a patch. Here, using social search enables foraging agents to rely on the sampling of other agents (in addition to their own), thus reducing sampling error. Further, as more agents gather in high resource concentration areas, agent densities become a better indicator of resource availability. In environment 7, because resources are distributed in extremely clean clusters, agents can directly sense and move toward locations of high resource concentration relatively easily, so that a high social search parameter value may be of less benefit. Moreover, agents may instead benefit from avoiding competition in such patches, leading to greater selection of social search parameter values below 0 (as suggested by the wide distribution of this parameter in environment 7). On the other hand, in the lower cluster conditions (environment 4 and below), resources are too noisy for social search to be beneficial—there are not enough well-defined clusters to exploit and share—leading to low evolved parameter values.

These potential benefits of social foraging in partly noisy environments of resource concentrations are related to those investigated by Grünbaum (1998). On the basis of a simulation model combining individual search with social cues, he suggested that phytoplankton-consuming fish such as krill and anchovies engage in social taxis (attraction to others) because the aggregation of movement decisions helps in denoising perception of food concentrations.

Such ‘wisdom of the crowds’ is probably beneficial here because the relatively small sensing ranges of consumer agents are more susceptible to sampling errors. Therefore, it is possible that if the sensing capabilities of agents is improved, individual samples will have lower error, reducing the benefit, and hence evolution, of social search. We put this hypothesis to test by enhancing the sensory range of consumers, achieved indirectly through increasing the range over which resource and consumer odors diffuse. Figure 4B displays the distribution of social weights that evolve in varying patchiness conditions in simulations where odor diffusion of resources and consumers is wider, with the standard deviation of odor diffusion increased to 4.5 (from 1.5 in Figure 4A). Agents can thus collect wider samples of the environment, making them less susceptible to small-scale fluctuations. Now social search in cluster environments 6 and 7 is lower than that in Figure 4A and it peaks in the noisier environment 5. This fits well with the social denoising explanation—because of enhanced sensing of resources, individual sampling produces lower error in determining directions to abundant resources, so agents are less likely to benefit from social search in the two highest clustering conditions. Here, they may be better off avoiding competitors, leading to the increased evolution of negative social search values. Presumably, in cluster environments 4 and 5 the level of environmental noise is high enough that social search remains beneficial.

We also ran a third set of simulations—here odor perception for resources is returned to original values (as in Figure 4A) but social odor perception is kept high (as in Figure 4B). Therefore, odors of food diffuse with SD 1.5 but odors of other consumers diffuse with SD 4.5 and so can be reliably sensed over a greater distance. Here, we expect that social search should provide enhanced benefit in reducing error of individual sampling across all environments and should therefore be selected for. This is borne out in Figure 4C, where agents evolve higher values of social search weights than in Figure 4A.

The ranking of sensing abilities simulated in Figure 4C—where agents can detect other foragers from a greater distance than food—is common in the natural world. For instance, animals tend to be bigger than the food they consume and hence are visible from a larger distance and birds can often hear calls of other birds indicating their locations from further off than they can sense food (Greig, Taft, & Pruett-Jones, 2012). Often such a difference in perception evolves as a cooperative strategy in species (as in the latter example regarding birds above; Bouhlel et al., 2018). The current simulations suggest why such cooperative strategies provide considerable adaptive benefit—cooperating with other agents by indicating one’s location and furthering each individual’s perceptual radius overall helps denoise fuzzy clusters of food.

**Experiment 2: Fixed Social Search**

In the second experiment we manipulate the search strategy and observe the resource distribution that emerges in response to the consumption patterns produced by the fixed search strategy. As mentioned earlier, we expect to find that social search increases the patchiness of the world through collective overconsumption of some resource localities along with underconsumption of others.
Across conditions, we fixed social search at levels corresponding to consumer odor weights between -1 and +1 in 0.25 intervals (the resource odor weight was kept at +1 throughout). As in Experiment 1, ten 1000-step-long simulations were run for each condition and patchiness values from the last 200 steps are presented here. Clustering levels of resources were measured as described in the Methods, with higher values indicating greater clustering.

**Results and Discussion**

Figure 5 displays the distribution of measured clustering values across various social search conditions. We find that as social search increases, clustering also increases, up to a point. In very high social search conditions (≥ 0.75), clustering appears to decrease. The inverted U-shaped curve resembles our results from Experiment 1 (Figure 4A).

The general trend of increased clustering with greater social search appears as hypothesized—consumers being moderately attracted to other consumers (social search weights around .1 to .5) produces regions of high popularity (and overconsumption—hence resource “deserts”) interleaved with regions of low popularity (and underconsumption, yielding resource patches), while asocial search (∼0) and competition repulsion (< 0) produce more even consumption of resources across the landscape and so less patchiness.

The dip in clustering levels at very high values of social search was unexpected. It is possible that these extremely social agents have inefficient movement toward resources due to their relatively large tendencies of clustering together. As a result, more of the world is left unconsumed and fertile and fewer overexploited regions exist (yielding more evenly distributed resources). Along these lines, Grunbaum (1998) suggests that excessive schooling tendencies can make the school less effective at changing directions toward resource gradients and therefore reduces overall consumption. To verify this, we compared the average resource consumption between when social search was set at 1 and at 0.5, finding a small but significant (p<.5) decrease at the higher social search value.

It must be noted that in all conditions, the average clustering metric is above 0.22 and even in the lowest social search condition, the world looks visually patchy. This is in line with our previous study finding that simple asocial movement toward resources can also produce resource patchiness (Luthra et al., 2020). Our current results show that social attraction serves to increase such patchiness.

We often observe the consequences of such socially-induced clustering in cultural domains—for instance, clothing styles are heavily influenced by what is popular or trendy, producing “overconsumption” of certain localities of the multidimensional clothing-style landscape (i.e., clustering). Here, the level of social (versus individual) search is generally high because of the desire to fit in with current fashion trends displayed by others. Unlike our simulations, in such cultural domains, the resources may be effectively inexhaustible (clothing styles do not disappear upon consumption)—however, overconsumption does often reduce their attractiveness to the extent that cultural resources gain value from their distinctiveness.

In all our simulations, we also find that locations of resource fertility and consumer density change across time—that is, they are temporally patchy in addition to being spatially patchy. Specifically, sections of the world experience bursts of “popularity” followed by inactivity. This is depicted in Figure 6—the blue line plots the popularity of a 10 × 10 unit section of the world (measured as the number of consumers in that section) against timesteps for the 0.5 social search condition. As can be seen, there are sudden spikes in the number of consumers in that region interleaved with lulls. This finding is not surprising—as that region increases in fertility, it becomes attractive to agents; given the high social search weights, those agents attract more agents, leading to popularity spikes. Once that patch loses fertility, agents move out of it, producing inactivity.

Interestingly, similar temporal dynamics of popularity are
again found in several cultural domains—information on social media, Wikipedia pages, and dog breeds display similar popularity bursts (Herzog, Bentley, & Hahn, 2004; Ratkiewicz et al., 2010). Analyses of these dynamics find that popularity values across time follow a power-law distribution, characterized by high frequency of low popularity and a heavy-tailed low frequency distribution of high popularity (e.g., prevalence of individual celebrities in popular media is often bursty across time). Studies partly attribute such burstiness to rich-get-richer mechanisms produced by social search (e.g., media attention to a celebrity produces even more attention; Ratkiewicz et al., 2010). We investigated this relationship in our simulations by calculating the burstiness of popularity of 10 × 10 unit sections of the world across time for different social search conditions using the burstiness measure defined by Goh and Barabási (2008):

\[ B = \frac{\sigma - \mu}{\sigma + \mu} \]

where \( \sigma \) and \( \mu \) denote the standard deviation and mean of popularity of the 10 × 10 sections. Figure 7 displays the distribution of burstiness values across varying social search conditions. We see that bursty popularity of the world follows a trend similar to that of clustering in Figure 5—as social search increases from -1 to around 0.25 or 0.5, burstiness generally increases; but at very high social search parameters (0.75 and 1), burstiness is lower. Figure 6 plots popularity against time for the two social search conditions with the extreme burstiness—as can be seen, popularity bursts are more intense for 0.5 social search and comparatively lower for -1 social search. Further, while the burstiness distributions generated by positive values of social search were best fit by the power-law distribution, negative values were better fit by less heavy-tailed distributions (e.g., exponential), indicating a role of social search in power-law temporal dynamics. Luthra and Todd (in press) conducted more detailed analyses of such burstiness, finding that social search induced power-law distributed popularity bursts not only across time, but also across space (i.e., at a particular timestep, certain regions of the grid experienced popularity bursts).

### Experiment 3: Emerging Resource Distribution and Evolving Social Search

In the previous two studies, we analyzed the unidirectional influence of resource distribution on social search and vice versa, finding that increases in each produces increases in the other (up to some threshold). In the third experiment, we investigate the dynamics of systems where both resource distribution and social search are left unconstrained and free to influence the other. In many real-world systems, neither resource patchiness nor social search is entirely fixed; rather, each is at least slightly responsive to the other. Consumers learn or evolve optimal social search levels in their environments and resources change in density across space and time based on consumption behaviors produced by consumer search strategies. The current simulations allow us to analyze the outcomes of such systems.

### Results and Discussion

Figure 8 displays the average social search and resource clustering values in the world across one simulation run. In these simulations, social search parameters start at random values across the consumer population and resources start randomly distributed around the world—hence, starting values of mean social search weight and the resource clustering metric are both 0 (but neither are constrained to 0). As can be seen, after some initial fluctuations, both eventually stabilize to positive values—in the last 200 timesteps, average social search weight is 0.26 and average clustering is 0.32. We ran a total of ten simulations, obtaining similar results. These results seem to suggest that both social search and clustering are stable states of the world when allowed to freely interact.

Results from the previous two experiments allows us to interpret these further findings. In Experiment 2, we found that clustering stably evolves across all social search levels—even at -1 social search, we obtained an average clustering of 0.2. Experiment 1 showed that increases in clustering produces increases in social search. It appears that once the world is somewhat clustered, both clustering and social search
escalate until they reach some threshold. This threshold is potentially the result of the inverted U-shaped pattern of parameter interaction observed in the previous two experiments—in both experiments we found that extremely high levels of one parameter reduces the other. This potentially produces stabilizing effects in the current simulations. These results help explain why social search and resource patchiness are ubiquitous in the real world—in a random system where the two are allowed to freely interact, they each produce escalations of the other, which stabilize upon reaching some threshold.

As a final analysis, we investigated how resource-search dynamics are influenced by depletion properties of resources. Across domains, resources vary in how quickly they deplete— for instance, informational resources (like YouTube videos) do not deplete when consumed by others (though their attractiveness might reduce with overconsumption), but food resources deplete relatively quickly. We expected that resources that deplete more slowly would yield more benefit for social search, as agents would have time to move to where they sense other agents before the other agents have consumed as much of the local resources. We ran two variations of simulations where resources had different depletion rates—for each energy unit of resources consumed either 1.5 or 0.5 energy units of the resource would actually disappear from the resource. We observed a stable difference in social search between these conditions (significant at p<.05): As expected, when resources deplete slowly (depletion rate = 0.5), social search evolves to high attraction levels, reaching 0.41; but when resources deplete faster (depletion rate = 1.5), social search reduces to -0.13, indicating avoidance among agents. It appears that stable states of social search are dependent on characteristics of the search domain, such as exhaustibility—relatively inexhaustible resources (like information) promote more social search while quickly depleting resources can promote competitive repulsion.

**General Discussion and Conclusions**

Our studies systematically analyzed mutual interactions between social search and resource clustering or patchiness. In Experiment 1, we varied resource clustering in the world and observed its influence on the evolution of social search. In Experiment 2, we observed the influence of social search on resource distribution. In both these experiments we found that increasing levels of one variable produced increases in the other; however, at very high levels of the manipulated variable, the dependent variable tended to fall. In our final experiment, we studied the dynamics that arose when resource clustering and social search freely interacted with each other. Resources started randomly distributed and social search parameters started at random values. Across time, both mutually interacted and changed the values of the other, stably evolving to positive levels of social search and patchiness (Figure 8). The inverted U-shaped pattern of interaction observed in Experiments 1 and 2 (Figures 4A and 5) produced a self-organizing system wherein each parameter stabilized the values of the other.

These results fit with previous experiments indicating that social search is adaptive under clustered environments. Going beyond those previous findings, we also show that some fuzziness in the environment distribution produces greater adaptive pressure for the evolution of social search than clean clusters—in noisy clustered environments, consumers evolve to strengthen their assessment of resource locations by combining their error-prone small perceptual samples with samples of other consumers. In environments with very high clustering and little noise, small individual samples were reliable estimates of the environment, reducing the need for social search. Across all environments, enhancing the ability to perceive other consumers increased benefits of social behavior—this explains the real-world ubiquity of cooperative social search, where consumers reveal their location from a greater distance to mutually benefit search of food (e.g., birds vocally communicate their locations).

Similarly, we found that clustering was highest when social search was fixed at moderate positive values; however, very high social attraction appeared to impede consumers, leading to fewer overconsumed regions and lower patchiness overall. These results are reflective of search in the cultural domains where social search is typically high—following others very closely in a cultural resource landscape (e.g., clothing choices) produces patchy utilization of that landscape (e.g., fashionable clothing trends). In these simulations we also find that social search not only produces patchy spatial dynamics, but also corresponding patterns of patchy temporal dynamics. Specifically, we find evidence for bursty popularity of patches that were best fit by a power-law distribution. Such temporal dynamics are again characteristic of cultural domains high in social search (e.g., social media, Ratkiewicz et al., 2010).

Finally, we found that positive (although low) values of social search and resource clustering were stable states of our model when both were allowed to freely interact. This result is particularly significant because in most real-world scenarios, the two variables are not strictly fixed. At least to some extent, consumers adapt their search strategies to what is optimal in their environment and the environment changes depending on the resulting consumption behavior. Most previous work has focused on unidirectional interactions between the two variables, failing to account for scenarios where structure in the world emerges from a dynamical mutual interaction between them. Our studies demonstrate that in such a scenario, social search and resource clustering can be stable attractor states, emerging even in simulations where both start at random values. However, we find that these stable values can differ depending on characteristics of the search domain—specifically, if resources are less exhaustible (like information on the internet) higher stable values of social search can result, while rapidly depleting resources can produce consumer repulsion from competition.

Despite using a relatively simple search model—with only one evolving parameter and two agent types in a two-dimensional landscape—the rich dynamics that arise can be explored to shed light on behaviors and patterns in a wide range of search domains, from food foraging in 2- and 3-dimensional landscapes to cultural and information search in highly multidimensional spaces. Our results emphasize the similarity of search-sociality-environment dynamics across these domains—further investigations of these dynamical systems can enable us to make useful predictions of consumer search and resource behavior.
Supplemental Materials

Supplemental materials, code, and data for this project are available online at https://github.com/mahiluthra/social-search-clustering

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