# Bite off what you can chew?

# Knowledge acquisition strategy and the evolution of absorptive capacity

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## Abstract

This study examines a common assumption in the literature on organizational learning that an exploitative knowledge acquisition strategy will accumulate less diverse knowledge than an explorative strategy. We show that the advantages of explorative knowledge acquisitions fade when taking into account factors that influence the ease of knowledge acquisition, such as sensitivity of absorptive capacity to knowledge distance, requirement for repeated engagements with particular knowledge, and depreciation of knowledge due to forgetting. Our results show that an exploitative knowledge acquisition strategy can outperform an explorative knowledge acquisition strategy both in terms of the success rate for knowledge acquisition and the diversity of the resulting knowledge stock.

## 1. Introduction

In this study, we examine how the choice of knowledge acquisition strategies (i.e. the choice between attempting to acquire local or distant knowledge) affects the success of knowledge acquisition and the diversity of the acquired knowledge stock. Acquiring new knowledge is an important factor for a firm to stay innovative. Knowledge and learning is vital for the adaptiveness, innovativeness, performance, and survival of firms Brown and Duguid, 1991; Chaney and Devinney, 1992). Further, it is core to many theoretical frameworks such as absorptive capacity (Cohen and Levinthal, 1990), dynamic capabilities (Teece, Pisano and Shuen, 1997), entrepreneurial expertise (Sarasvathy, 2001). The acquisition of new knowledge, while crucial, is not an easy task. March (1991) argues that firms face the choice between exploitative knowledge acquisition that fosters the acquisition of local knowledge and explorative knowledge acquisition strategies that aims at acquiring distant knowledge. Here we explain that the relationship between firms' knowledge acquisition strategies and acquisition success that March assumes is contingent on several organizational and environmental factors.

In particular, we look at how strategy directs choice in knowledge acquisition, and how over time it shapes the organization's knowledge stock and subsequently absorptive capacity (Cohen & Levinthal, 1990), which themselves are important resources in knowledge acquisition. We thus conceptualize organizational learning as a continuous feedback loop, in which we treat knowledge acquisition *strategy* as a stable exogenous attribute but knowledge acquisition *process* and *outcome* as endogenous and perpetually evolving. Our approach emphasizes the evolutionary nature of the learning process, which points to the malleability of absorptive capacity over time. In this regard, we follow a long line of theoretical and empirical work that draws attention to the recursive element of absorptive capacity (e.g., Ahuja, 2000; Cockburn & Henderson, 1998; Lane & Lubatkin, 1998; Lyles & Salk, 1996; Pennings & Harianto, 1992; Pisano, 1994; Shane, 2000; Stuart, 1998).

Based on this approach, we build a computational model to offer some insights into a common problem in organizational learning: When should organizations make persistent attempts to acquire local versus distant knowledge? We review below why organizations face this choice and why a particular knowledge acquisition strategy may or may not lead to its intended outcome. In our model, we identify four organizational and environmental factors that affect knowledge acquisition success. First, distance sensitivity takes into account that distant knowledge is more difficult to acquire than local knowledge. Second, Magnitude sensitivity is a function of repeated engagement. This factor takes into account that the likelihood to acquire new knowledge increases with repeated exposure and use. Third, age sensitivity assumes that the organizational memory is not perfect and reflects the process of forgetting. Finally, environmental diversity reflects the density of knowledge in a firm's environment and affects all three organizational factors.

### 1.1. Exploitative and explorative strategies in knowledge acquisition

Knowledge acquisition strategy can be characterized according to a dimension with two extremes: exploitative and explorative (March, 1991). A purely exploitative organization is one that chooses to acquire new knowledge that is as local as possible to its existing knowledge stock (cf. Cyert & March, 1963; Gavetti & Levinthal, 2000;

March & Simon, 1958), whereas a purely explorative organization is one that chooses to acquire new knowledge that is as distant as possible. In reality, organizations adopt a knowledge acquisition strategy that resides somewhere in between these two extremes (Katila & Ahuja, 2002). An organization's choice in knowledge acquisition may therefore be positively or negatively correlated to the contents of its knowledge stock; an exploitative strategy can be viewed as diversity avoiding and an explorative strategy diversity seeking.

Each of the two knowledge acquisition strategies above has its benefits and limitations. Organizations may lean toward being exploitative for a number of reasons, such as to minimize knowledge acquisition and integration costs (Dosi, 1988; Grant, 1996), as well as to increase the chances of synergy among existing knowledge bases (Henderson, 1994). Consistent with these lines of reasoning, Helfat (1994) found that firm-level R&D investments become more focused over time in a path-dependent manner. Furthermore, Stuart and Podolny (1996) found that even in the face of major technology shifts, firms often made only limited adjustments to the scope of their technological search. A limitation that is frequently attributed to the exploitative strategy is that it can lead organizations to develop 'core rigidities' (Leonard-Barton, 1992) or fall into 'competency traps' (Levitt & March, 1988). Furthermore, since the exploitative strategy can be viewed as diversity avoiding, it may limit an organization's combinative capability (Kogut & Zander, 1992) such that it generates mostly incremental rather than breakthrough innovations (Dewar & Dutton, 1986).

The explorative knowledge acquisition strategy, on the other hand, is often lauded as being important for organizational performance and survival due to its promise of bringing into the organization distant knowledge that can be recombined to produce breakthrough innovations (Fleming, 2001; Rosenkopf & Nerkar, 2001). Many illustrative examples of such innovations have been documented in the literature: Merrill Lynch developed its approach to retail brokerage by borrowing ideas from the supermarket business (Gavetti, Levinthal, & Rivkin, 2005); IDEO designed the articulating ball-and-socket joint design for desk lamps based on principles in human hip-bone sockets (Hargadon & Sutton, 1997); Qualcomm developed its revolutionary mirasol® color display technology by studying the microstructures of *Morpho* butterfly wings (Graham-Rowe, 2008). Nevertheless, the explorative strategy is often a risky one to follow. The value of distant knowledge is often difficult to ascertain not only due to its relative unfamiliarity, but also because its expected payoff is subject to much uncertainty. For example, when the desired outcome of an explorative knowledge acquisition strategy is a novel and game-changing technology, many variables beyond a single organization's control may turn out to be critical, such as market and customer acceptance of the technology, the adoption and diffusion of it, and competitors' strategic actions (Fleming, 2001; Rosenberg, 1996).

The choice between exploitative and explorative knowledge acquisition strategies is a difficult one for organizations not only due to the trade-offs discussed above, but perhaps most importantly, because organizations have limited resources such that pouring resources into one strategy often means depriving the other (March, 1991). Furthermore, in deciding on knowledge acquisition strategies in general, there are other factors to consider, such as whether knowledge stickiness would be a significant impediment (Szulanski, 2003), whether the organization is equipped with the right structure for the choice of strategy (Nickerson & Zenger, 2005), whether the competitive environment in which the organization operates is a better fit for one strategy versus another, and relatedly, whether it is even possible to accurately infer the state of the environment (Posen & Levinthal, 2012).

### 1.2. Framework: Absorptive capacity, knowledge acquisition strategy, and outcome

Despite the aforementioned variety of considerations, one unifying assumption in evaluating the choice between exploitative and explorative knowledge acquisition strategies is that the former will indeed result in the accumulation of local knowledge, and the latter distant knowledge. This assumption is worth revisiting, however, because in reality the implementation of a knowledge acquisition strategy does not always lead to its intended outcome. Organizations often deliberately seek distant knowledge only to find themselves acquiring local knowledge yet again. As documented by Monteiro (2009), many multinational corporations attempt to acquire distant knowledge through their subsidiaries around the globe and yet are frequently unable to convert on the opportunities to do so. Conversely, organizations that deliberately focus on local knowledge sometimes find themselves successfully acquiring and even developing new knowledge in a completely different domain. For example, Kao's local knowledge of surfactant (soap) technologies led it to develop a better coating for floppy disks (Rosenkopf & Nerkar, 2001). These instances thus raise the interesting question of whether the path to distant knowledge is sometimes paved by an exploitative knowledge acquisition strategy, and vice versa.

Absorptive capacity is our guiding framework in investigating this question. Of the different components of its definition, i.e., the ability to evaluate, acquire, and apply new knowledge towards commercial ends (Cohen & Levinthal, 1990), We focus on the acquisition component. A fundamental principle in this framework is that an organization's absorptive capacity is shaped by the characteristics of its knowledge stock (Cohen & Levinthal, 1990, Volberda, Foss, & Lyles, 2010). Learning takes place in a cumulative fashion (Bower & Hillgard, 1981; Lindsay & Norman, 1977) such that prior related knowledge in an organization's knowledge stock is important for new knowledge acquisition. The value of prior knowledge is not only due to its content per se, but also the relevant learning skills that were accumulated as a result of prior knowledge acquisition (Ellis, 1965; Estes, 1970).

In familiar and stable contexts, the type of prior related knowledge that is important for successful knowledge acquisition tends to be clear, whereas in novel and uncertain contexts, it tends to be difficult to predict ex-ante (Tushman & Anderson, 1986). In the latter, diversity in a knowledge stock can thus become a source of competitive advantage. As Cohen & Levinthal (1990:131) explained: "In a setting in which there is uncertainty about the knowledge domains from which potentially useful information may emerge, a diverse background provides a more robust basis for learning because it increases the prospect that incoming information will relate to what is already known. In addition to strengthening assimilative powers, knowledge diversity also facilitates the innovative process by enabling the individual to make novel associations and linkages."

The absorptive capacity framework allows us to surmise that an exploitative organization is likely to be successful in the early stage of its knowledge acquisition attempts because its choice of new knowledge rarely strays far from its prior knowledge. Such an exploitative organization is able to quickly amass a large body of closely related knowledge. It may then be able to use it to acquire increasingly distant knowledge, one step at a time. It is also possible, however, that such an exploitative organization ends up becoming a prisoner of its own knowledge, never generating enough diversity in its knowledge stock to venture beyond local knowledge. An explorative organization, on the other hand, can be expected to have some difficulty acquiring knowledge in its earlier attempts. This difficulty may persist such that it becomes permanently stuck as a poor acquirer of knowledge. An alternative and more optimistic outlook is that it may eventually accumulate a diverse enough knowledge base to improve future acquisition success. Which of these alternative scenarios plays out likely depends on factors beyond absorptive capacity itself.

For instance, the outcome of a knowledge acquisition strategy likely depends on the characteristics of the environment (Argote, McEvily, & Reagans, 2003). As intuition would suggest, an explorative strategy would not work well in a knowledge acquisition environment that does not offer diverse knowledge; an explorative organization in such an environment simply would not be able to satisfy its appetite for distant knowledge. Similarly, an exploitative strategy might not work well in a knowledge acquisition environment that is too diverse; an exploitative organization in such an environment might have difficulty finding new knowledge that is local enough in relation to its existing knowledge stock. It should also be noted, however, that when the knowledge acquisition environment is more diverse, an exploitative organization might also be able to find knowledge that is more local to its existing knowledge stock.

Diversity of new knowledge in a knowledge acquisition environment is sometimes a function of density (cf. Hansen & Haas, 2001), which can be understood as volume of knowledge per unit space and time. Density implies the availability of options: At the most fundamental level, it allows an organization to acquire any new knowledge at all. A barren environment of very low density can inhibit knowledge acquisition irrespective of strategy. Conversely, assuming non-zero level of diversity, greater density in a knowledge acquisition environment improves the chances that an organization can find what it truly prefers. In a high-density environment, an exploitative organization is likely to be able to find knowledge that is extremely close to its existing knowledge stock, whereas an explorative organization is likely to be able to find knowledge that is extremely distant to its existing knowledge stock.

By investigating the interrelationships among knowledge acquisition strategy, knowledge stock, absorptive capacity, and knowledge acquisition environment, we contribute to the organizational learning literature on at least two fronts: First, we offer insights on why there is sometimes a discrepancy between knowledge acquisition strategy, which implies an intended outcome, and actual outcome. Second, we unpack the mechanism of knowledge acquisition to show how a particular knowledge stock configuration is generated over time. While various streams of research have demonstrated the link between knowledge stock characteristics and organizational performance (e.g., Brusoni, Prencipe, & Pavitt, 2001; Hargadon & Sutton, 1997), less is known about how to obtain a desired knowledge stock configuration.

## 2. The mechanism of knowledge acquisition

Figure 1 summarizes three main processes in our conceptual model: First, an organization's knowledge stock and knowledge acquisition strategy co-determine its knowledge choice. Second, the organization's knowledge stock determines whether the chosen knowledge can be successfully acquired. Third, if the attempted acquisition is successful, the newly acquired knowledge contributes to and reshapes the organization's knowledge stock. As shown in the figure, we highlight the role of absorptive capacity in the second process.[1] It represents the organization's ability to actually acquire knowledge that it chooses to acquire.

----- Insert Figure 1 about here -----

### 2.1. Distance sensitivity

In our model, absorptive capacity is primarily a function of the distance between the organization's new knowledge of choice and its existing knowledge stock. The greater the distance, the more difficult the new knowledge is to acquire (Pennings & Harianto, 1992). Several factors may modulate this relationship. For example, different knowledge acquisition contexts may render absorptive capacity more or less sensitive to distance; prior related knowledge may be more or less crucial for acquisition success in some disciplines or circumstances than in others. Knowledge acquisition in basic science, for instance, typically requires more closely related knowledge compared to knowledge

[1] Absorptive capacity also plays a role in the first and third process, i.e., the evaluation of new knowledge and the assimilation of newly acquired knowledge into an organization's knowledge stock, but this is beyond the scope of this paper.

acquisition in applied science (Page, 2007: 119-127). Sensitivity to distance may also be influenced by certain organizational characteristics distinct from sheer knowledge stock, such as material resources, prior experience with knowledge search, network position, combinative capability, organizational form, organizational size, and group characteristics within the organization (Almeida, Dokko, & Rosenkopf, 2003; Fosfuri & Tribó, 2008; Haas, 2006; Haas, 2010; Lavie & Rosenkopf, 2006; Powell, Koput, & Smith-Doerr, 1996; Rosenkopf & Almeida, 2003; Van den Bosch, Volberda, & Boer, 1999).

We assign a parameter called *distance sensitivity* to take into account such factors that can influence the sensitivity of absorptive capacity to distance. As such, given greater distance sensitivity, an exploitative organization would be much more likely to prefer and successfully acquire more local knowledge; and when it does try to acquire distant knowledge, it is unlikely to succeed. Conversely, given greater distance sensitivity, an explorative organization would be much more likely to prefer more distant knowledge. The twist, however, is that it is unlikely to succeed at acquiring it.

### 2.2. Learning curve: Magnitude and age

Independent of distance to new knowledge, the intrinsic characteristics of an organization's knowledge stock itself also matters for absorptive capacity. Research on learning curve suggests two main factors influence the ease of knowledge acquisition and thus absorptive capacity: the magnitude and age of existing knowledge (Darr, Argote, & Epple, 1995; Dutton & Thomas, 1984; Hayes & Clark, 1986; Yelle, 1979).

#### 2.2.1. Magnitude sensitivity

Knowledge magnitude is a function of repeated engagement. Not all types of knowledge in an organization's knowledge stock get accessed or utilized with equal frequency or intensity; an organization tends to engage with certain types of knowledge more intensively than with others (Levitt & March, 1988; Nelson & Winter, 1982). In some contexts, the types of knowledge that enjoy a greater level of engagement may become more influential in driving the organization's knowledge acquisition outcome. For instance, repeated engagement with knowledge via deliberate practice is perhaps more critical for further knowledge acquisition in a large airline than in a small technology startup; the former organization operates in a complex yet relatively stable landscape, in which knowledge domains tend to have more precise and enduring interrelationships, whereas the latter operates in a rapidly changing landscape, in which knowledge domains and their interrelationships are constantly being redefined (Posen & Levinthal, 2012).

To take into account the effect of engagement on absorptive capacity, we assign a *magnitude sensitivity* parameter. Assuming positive distance sensitivity, an exploitative organization whose knowledge acquisition context is characterized by greater magnitude sensitivity would be much more likely to prefer and successfully acquire knowledge that is more local and with which it has engaged more. Conversely, an explorative organization in the same context would be much more likely to prefer knowledge that is more distant and with which it has engaged less. Like the exploitative organization, however, such an explorative organization would still be much more likely to successfully acquire local knowledge with which it has engaged more.

**2.2.2. Age sensitivity**

Knowledge age is defined as the temporal distance between the present and the time of acquisition. Organizations presumably do not have infinitely persistent and reliable memory; knowledge tends to depreciate over time due to individual memory deterioration, imperfections in knowledge management systems, and employee turnover (Darr, Argote, & Epple, 1995). Furthermore, recency of knowledge in the knowledge stock also tends to influence attention and preference (Levitt & March, 1988). Variance in these factors suggests that an organization's absorptive capacity may be more or less sensitive to the age of knowledge in its knowledge stock.

To take into account the effect of knowledge age on absorptive capacity, we assign a parameter called *age sensitivity*. An exploitative organization with greater age sensitivity would thus be much more likely to prefer and acquire new knowledge that is more local, particularly in relation to its more recently acquired existing knowledge. An explorative organization with greater age sensitivity, on the other hand, would be much more likely to prefer but less likely to successfully acquire new knowledge that is more distant, particularly in relation to its more recently acquired existing knowledge.

### 2.3. Effects of knowledge acquisition environment diversity on absorptive capacity

Diversity of the knowledge acquisition environment is expected to influence absorptive capacity differently with regards to distance sensitivity, magnitude sensitivity, and age sensitivity. We explain each relationship below:

#### 2.3.1. Environment diversity and distance sensitivity

In a more diverse knowledge acquisition environment, an exploitative organization can choose and then attempt to acquire knowledge that is more local to its existing knowledge stock. Conversely, an explorative organization can choose and then attempt to acquire knowledge that is more distant to its existing knowledge stock. The expected effect of environment diversity on the acquisition success of these opposing strategies is thus straightforward: Greater diversity will result in greater acquisition success for exploitative organizations, but it will hurt explorative organizations.

### 2.3.2. Environment diversity and magnitude sensitivity

In a more diverse knowledge acquisition environment, any organization, irrespective of strategy, is expected to have greater difficulty repeatedly engaging with a single type of knowledge. Given some positive value of magnitude sensitivity, greater environment diversity thus lowers the probability of acquisition success. When both magnitude sensitivity and distance sensitivity are positive, greater environment diversity should hurt the explorative organization even more since now it is even less likely to repeatedly engage with a single type of knowledge.

### 2.3.3. Environment diversity and age sensitivity

As long as distance sensitivity is zero, greater diversity together with age sensitivity should have no impact on acquisition success for any type of strategy. When both distance sensitivity and age sensitivity are positive, however, greater environment diversity should hurt the explorative organization because now it is more likely to choose and then fail to acquire more distant knowledge. This subsequently increases the likelihood that it has no recently acquired knowledge in its knowledge stock, which further hurts its probability of future acquisition success. The opposite is expected for the exploitative organization: Greater environment diversity allows it to successfully choose and acquire more local knowledge. This subsequently increases the likelihood that it always has recently acquired knowledge in its knowledge stock, which improves its probability of future acquisition success.

## 3. Model specifications

The model is composed of a nested hierarchy of three components: (1) a *knowledge universe*, which stores information about the relatedness of all knowledge domains, (2) a *knowledge acquisition environment*, which contains a subset of the knowledge universe, and (3) an *agent* (i.e., an organization) that operates inside the knowledge acquisition environment and possesses its own *knowledge stock*. Figure 2 provides an illustrative overview of these three components.

----- Insert Figure 2 about here -----

### 3.1. Knowledge universe

The knowledge universe is a map that represents the network of connections among all knowledge domains. The map thus provides some information about how far apart or closely related a given pair of knowledge domains is.

The model assumes that the knowledge universe is a *true* map. In other words, it is not subject to an agent's perception or mental model. As such, there is only one knowledge universe. An agent has only an imperfect idea about where various neighborhoods of knowledge domains are located and how they are organized. The extent to which an agent understands the map is a function of the agent's own knowledge stock. For example, if an agent possesses some knowledge about nanotechnology, then the agent should have some idea about where the neighborhood of nanotechnology is located relative to other neighboring knowledge domains, and a less clear idea about knowledge domains that are further away.

As illustrated in Figure 2, the knowledge universe takes the form of an undirected, scale-free network that is generated via a preferential attachment process (Barabási & Albert, 1999). The growth process starts with an initial network of two connected nodes. New nodes are then added to this network one at a time. Each new node selects an existing node to which it then connects.[2] The probability $p_i$ that an existing node $i$ gets selected by the new node is proportional to node $i$'s degree $k_i$, such that:

$$p_i = \frac{k_i}{\sum_{j=1}^{n} k_j} \quad [1]$$

where $n$ is the number of existing nodes in the knowledge universe network at the time $p_i$ is calculated. New nodes continue to be added to the network until the total number of nodes equals to $N$. $N$ is thus the size of the knowledge universe.

Our choice of representing the knowledge universe as a scale-free network that is grown via preferential attachment is based on two reasons: First, a large body of empirical research has demonstrated that two classes of knowledge-related networks—information and collaboration networks—frequently have a scale-free topology. Some

[2] A consequence of this process is that there is no isolate or "island" in the model. Since it is difficult to imagine a knowledge domain in reality that is completely isolated from everything else, this feature of the model appears reasonable.

examples of such networks are: the World Wide Web (Barabási, Albert, & Jeong, 2000), Wikipedia entries (Cappoci, Servedio, Colaiori, Buriol, Donato, Leonardi, & Caldarelli, 2006), scientific co-authorships (Newman, 2001[a]; Newman, 2001[b]), and Hollywood actor collaborations (Barabási & Albert, 1999).

Second, preferential attachment appears to be a reasonable mechanism for describing the growth and evolution of a knowledge network. Knowledge presumably evolves in a "rich-get-richer" manner. Knowledge domains that have a relatively large number of connections to other domains tend to be more visible and well-understood such that they are more likely to become the building blocks for the development of future knowledge domains.

Given that the knowledge universe is represented as a network, it is important to clarify what the nodes and links represent: The nodes represent knowledge domains, and the links represent the *relevance* between knowledge domains. Based on Gorayska and Lindsay's (1993) work, we define relevance in terms of functional relationships: Two knowledge domains are relevant to each other if one contains a means to some end that is embedded in the other. For example, evolutionary biology is relevant to organizational studies because it contains some concepts that help to accomplish the goals of organizational studies. The knowledge universe can thus be interpreted as a complete historical record of functional relationships among knowledge domains.

The definition of a knowledge domain—and therefore what a node represents—is more difficult to pin down: How granular does a knowledge domain need to be? Fortunately, the choice of scale-free topology offers a convenient solution: A scale-free network is self-similar (Song, Havlin, & Makse, 2005) such that the issue of granularity can be assumed away. If one were to zoom in to a neighborhood in the knowledge universe, that neighborhood would appear to have a structure that is similar to the structure of the overall knowledge universe. The generalizability of a conclusion drawn based on the knowledge universe is thus minimally compromised regardless of whether a node represents an entire discipline (such as management), a sub-discipline (such as operations), or a specific topic (such as just-in-time systems). Finally, it is important to note that our choice of representing knowledge domains as nodes in a network assumes that knowledge domains are generally comparable units.

### 3.2. Knowledge acquisition environment

The knowledge acquisition environment represents the knowledge space in which an agent can acquire knowledge. The knowledge acquisition environment consists of knowledge units, each of which has a location or "address" in the knowledge universe. (These knowledge units are thus simply replicas of a subset of nodes from the knowledge universe. In other words, each knowledge unit in the knowledge acquisition environment has a "parent node" in the knowledge universe.) The knowledge units are spatially scattered in the knowledge acquisition environment as unattached nodes, and their locations in the knowledge acquisition environment are independent of their parent nodes' locations in the knowledge universe (Figure 2).

When discussing knowledge in the knowledge acquisition environment, we use the term "unit" rather than "domain" for two reasons: First, the word "domain" implies a positional property of knowledge relative to other knowledge; in the knowledge acquisition environment, however, this property is not directly observable. Second, because there can be many replicas of the same knowledge domain in the knowledge acquisition environment, it would be imprecise to call each replica a knowledge domain.

Some real-world correlates of the knowledge acquisition environment are industries and geographic regions in which an organization operates. The knowledge acquisition environment can, however, have a broader and more abstract meaning. For example, the set of publications to which an organization subscribes or the set of alliance partners with which an organization interacts can also make up the agent's knowledge acquisition environment. The knowledge acquisition environment therefore has an agent-centric interpretation. (Although this does not necessarily imply that an agent has much control over the content of the knowledge acquisition environment.)

In the model, the knowledge acquisition environment is represented as a two-dimensional lattice of a fixed area (Figure 2). It has a *density* $E$; which is simply the total number of knowledge units that the knowledge acquisition environment contains since the area is of a fixed size.[3] The knowledge acquisition environment is set up according to a simple procedure: A node in the knowledge universe is randomly chosen to be replicated as a new knowledge unit in the knowledge acquisition environment, and this new knowledge unit is given a random $(x, y)$ coordinate. This process is repeated until there are a total of $E$ knowledge units in the knowledge acquisition environment. Each node in the knowledge universe can be replicated more than once, such that there may be multiple copies of knowledge units in the knowledge acquisition environment that have

[3] We choose to use the label *density* rather than *volume* because *density* leads to a better intuition about the agent's susceptibility to encountering new knowledge units in the environment.

the same parent node. According to this procedure, greater density implies greater diversity of knowledge units in the knowledge acquisition environment.

### 3.3. Agent

The agent represents an organization that first chooses and then attempts to acquire knowledge in the knowledge acquisition environment based on its knowledge stock. we explain each step below:

#### 3.3.1. Knowledge choice

The agent is assigned one of two knowledge acquisition strategies: exploitative or explorative. At $t = 0$, the agent occupies a random $(x, y)$ coordinate in the knowledge acquisition environment, and its knowledge stock is seeded with one initial knowledge unit. At each subsequent time point, the agent moves in a random direction in the knowledge acquisition environment. The agent then surveys all knowledge units within its radius of vision. Here, the radius of vision is fixed and set based on practical considerations; it is not so large that the simulation becomes too computationally demanding, but not so small that the agent does not have enough distinct knowledge units to survey at a given time point.

The agent assigns a probability $p_v$ to each knowledge unit $v$ within its radius of vision. The value of $p_v$ corresponds to the probability that the agent prefers knowledge unit $v$ over all other knowledge unit $w$ within the agent's radius of vision; $p_v$ is described by the following equation:

$$p_v = \frac{e^{nL_v}}{\sum_{w=1}^{V} e^{nL_w}} \text{ , } -1 \leq n \leq 1 \qquad [2]$$

where $V$ is the total number of knowledge units within the agent's radius of vision, $n$ is a constant, and $L_v$ (or $L_w$) is knowledge unit $v$'s (or $w$'s) distance (average path length) from all parent nodes of the knowledge units in the agent's knowledge stock. The constant $n$ can take a value between -1 and +1. For simplicity, if the agent's knowledge preference is exploitative, then $n$ takes a value -1, such that $p_v$ decreases as a function of $L_v$. And if the agent's knowledge preference is explorative, then $n$ takes a value of +1, such that $p_v$ increases as a function of $L_v$.

The computation of $L_v$ (and by analogy, $L_w$) takes into account the magnitude and age of the knowledge units in the agent's knowledge stock as described by the following equation:

$$L_v = \frac{\sum_{i=1}^{S} l_{vi}.e^{-g/c_i}.e^{-a_i f}}{\sum_{i=1}^{S} e^{-g/c_i}.e^{-a_i f}} \text{ , } c_i \geq 1, a_i \geq 0 \qquad [3]$$

Here, $l_{vi}$ is the path length between the parent node of knowledge unit $v$ and the parent node of knowledge unit $i$ in the agent's knowledge stock, and $S$ is the total number of knowledge units in the agent's knowledge stock. The term $e^{-g/c_i}$ assigns a weight to $l_{vi}$; $c_i$ is the number of copies (i.e., magnitude) of knowledge unit $i$ in the agent's knowledge stock, and $g$ is the magnitude sensitivity parameter. The term $e^{-a_i f}$ assigns a weight to $l_{vi}$; $a_i$ is the age of knowledge unit $i$ in the agent's knowledge stock, and $f$ is the age sensitivity parameter.

After each knowledge unit $v$ in the agent's radius of vision gets assigned a probability $p_v$, the agent runs a lottery based on the resulting probability distribution to choose a knowledge unit $j$ that it will attempt to acquire. In other words, knowledge unit $j$ is the agent's preferred knowledge unit.

### 3.3.2. Knowledge acquisition

The agent assigns a probability $p_j$ to knowledge unit $j$. The value of $p_j$ corresponds to the probability that the agent can actually acquire knowledge unit $j$; $p_j$ is described by:

$$p_j = 1 - \left\{ \prod_{i=1}^{S} \left[ 1 - e^{-\left(kL_{ij} + {}^{g}/_{c_i} + fa_i\right)} \right] \right\} \qquad [4]$$

where $k$ is the distance sensitivity parameter, $g$ is the magnitude sensitivity parameter, and $f$ the age sensitivity parameter. $L_{ij}$ is knowledge unit $j$'s distance from the parent node of a knowledge unit $i$ in the agent's knowledge stock.

## 4. Simulations

Based on the model specifications above, we run simulations to compare the two types of agents: exploitative and explorative. In all simulations, we keep track of two measures: *acquisition success rate*, which indicates whether an agent is able to acquire the knowledge unit that it chooses at each time point, and *average path length* of the knowledge units in the agent's knowledge stock, which is a proxy for diversity. We first establish baseline results by comparing the two types of agents as well as varying levels of environment density (which is correlated with diversity), all while setting the knowledge acquisition parameters of distance sensitivity $k$, magnitude sensitivity $g$, and age sensitivity $f$ to zero. We then vary each knowledge acquisition parameter individually and subsequently co-vary them with each other as well as with levels of environment density.

### 4.1. Baseline

The baseline results are as expected, which indicates that our model is set up appropriately. The exploitative and explorative agents show no difference in terms of acquisition success rate. Since distance sensitivity $k$ is set to zero, acquisition success probability is independent of the distance between the agent's new knowledge of choice and the agent's existing knowledge stock. In terms of average path length, both agents' knowledge stocks show an increasing pattern in the initial periods, but they quickly settle into a steady state (after ~15 periods), with the explorative agent settling at a higher average path length than the exploitative agent.

The effect of environment density is also straightforward: greater density means greater availability of knowledge units for agents to choose and subsequently acquire at each time step, which would improve acquisition success rate. Furthermore, greater environment density allows the exploitative agent to choose and then acquire knowledge that is more local to its existing knowledge stock, thereby lowering its average path length. Similarly, greater environment density allows the explorative agent to choose and then acquire knowledge that is more distant to its existing knowledge stock, thereby increasing its average path length.

### 4.2. Distance sensitivity

When distance sensitivity is positive, the exploitative agent performs better than the explorative agent in terms of acquisition success rate (Figure 3A). This is as expected, given that the exploitative agent chooses knowledge that is more local to its existing knowledge stock and thus easier to acquire. As such, distance sensitivity lowers both acquisition success rate and average path length for both exploitative and explorative agents. When distance sensitivity is low, the explorative agent enjoys an advantage over the exploitative agent in terms of average path length. As distance sensitivity becomes very large, however, this advantage diminishes since now the explorative agent is very likely to fail in acquiring distant knowledge (Figure 3B).

Greater environment density has opposite effects for exploitative and explorative agents. For the exploitative agent, greater environment density improves acquisition success rate as it allows the agent to choose and subsequently try to acquire more local knowledge. Consequently, the exploitative agent's average path length decreases with greater environment density as well. For the explorative agent, greater environment density hurts acquisition success rate as it allows the agent to choose and subsequently acquire more distant knowledge. The effect of environment density on the explorative agent's average path length is non-monotonic: Environment density increases the agent's average path length up to a point, but as environment density gets very high, the agent becomes very likely to choose and (unsuccessfully) attempt to acquire very distant knowledge, such that its knowledge stock consists mostly of relatively local knowledge, which results in a low average path length.

----- Insert Figure 3 about here -----

### 4.3. Magnitude sensitivity

When magnitude sensitivity is positive, acquisition success depends on prior repeated engagements with a particular knowledge unit. (In the model, such repeated engagements are represented in the agent's knowledge stock as multiple copies of knowledge units that come from the same parent node.) A positive magnitude sensitivity parameter thus creates a type of "friction" that slows down knowledge acquisition: The greater the magnitude sensitivity, the more an agent has to have repeatedly engaged with a particular knowledge unit in order to reach a given acquisition success probability. When magnitude sensitivity is very high, an agent can thus become permanently stuck with a low acquisition success probability.

Consistent with the reasoning above, our results show that greater magnitude sensitivity lowers acquisition success rate for all agents for a given time point, though it does not necessarily lower the final acquisition rate since all agents can reach (and settle into) ~100% acquisition success rate after many periods. When distance sensitivity is set to zero, positive magnitude sensitivity yields no significant difference between exploitative and explorative agents in terms of acquisition success rate. When distance sensitivity is positive, however, for a given magnitude sensitivity value, the exploitative agent wins over the explorative agent (Figure 4A). This is because the exploitative agent is now much more likely than the explorative agent to repeatedly engage with a particular knowledge unit. Greater magnitude sensitivity has a similar effect on average path length: It lowers average path length for all agents for a given time point, but it does not necessarily lower the *final* average path length for agents with the same knowledge acquisition strategy. When distance sensitivity is positive, however, greater magnitude sensitivity lowers the agent's average path length throughout all periods (Figure 4B), since now the acquisition probability favors not only knowledge units with which the agent has repeatedly engaged, but also those that are more local to the agent's existing knowledge stock.

----- Insert Figure 4 about here -----

Greater environment density has straightforward effects on both acquisition success rate and average path length: Greater environment density offers more choice, such that it becomes more difficult for an agent to repeatedly engage with the same knowledge unit, which in turn hurts acquisition success probability. In terms of average path length, greater environment density offers more extremes, both very local and very distant knowledge, such that it translates into lower average path length for the exploitative agent and higher average path length for the explorative agent. These effects are simply due to the agent's baseline differences; there is no meaningful interaction effect on acquisition success rate or average path length between environment density and magnitude sensitivity.

### 4.4. Age sensitivity

When age sensitivity is positive, the presence of recently acquired knowledge units in the knowledge stock is important for acquisition success. If an agent fails to acquire a knowledge unit in a given period, the agent's acquisition success probability in the next period is hurt. Thus, as long as the chance of an agent acquiring a knowledge unit in a given period is less than one, greater age sensitivity should translate into lower acquisition success rate for all agents. Our simulation results are consistent with this reasoning.

When distance sensitivity is set to zero, positive age sensitivity yields no significant difference between exploitative and explorative agents in terms of acquisition success rate. In terms of average path length, the exploitative agent is lower than the explorative agent, but this is due to baseline differences rather than age sensitivity. When distance sensitivity is positive, however, positive age sensitivity amplifies the effects of distance sensitivity both in terms of acquisition success rate and average path length. Both of these measures are now lower than when only distance sensitivity alone is positive (Figure 3 and Figure 5).

----- Insert Figure 5 about here -----

## 5. Limitations and extensions

The findings in this paper offer some insights into why knowledge acquisition strategies sometimes do not yield their intended outcomes, in particular why an explorative strategy may fail to accumulate diverse knowledge and even outperformed in this regard by an exploitative strategy (e.g., as shown in Figure 4). All of the parameters examined thus far, i.e., distance sensitivity, magnitude sensitivity, age sensitivity, as well as environment density, have the potential to hurt the explorative strategy more than they do the exploitative strategy. A takeaway here then is when any of the factors above is salient, an exploitative strategy may be a safer bet in terms of achieving acquisition success as well as diversity.

We hope that this paper contributes a systematic understanding of the interrelationships among knowledge acquisition strategy, knowledge stock, absorptive capacity, and knowledge acquisition environment. More specifically, the computational model presented in this paper offers some building blocks for future research on the roles of knowledge stock configuration in organizational learning, an important construct that may be challenging to study in the empirical setting alone.

Nevertheless, the findings in this paper reflect modeling choices and inevitably trade-offs, many of which were made in favor of tractability and at the expense of scope. We discuss below some limitations that result from those choices, the corresponding opportunities for extensions, and their potential contributions to the organizational learning literature:

**5.1. Static vs. dynamic knowledge universe**

The knowledge universe, which describes the relationship between knowledge domains, does not change throughout the course of the simulations described in this paper. New connections are never added, and existing connections are never severed. Likewise, new nodes are never added, and existing nodes are never deleted. The static nature of the knowledge universe in this paper implies that knowledge domains and their relationships to each other are constant, which of course is a simplification of a dynamically evolving reality.

A research question that cannot be answered using the current model is thus: How would knowledge acquisition strategies fare as the relationships between knowledge domains change? The state of knowledge may be rapidly evolving due to, for instance, new scientific discoveries, new technological developments, or new social conventions. A dynamic rather than static knowledge universe would first of all affect the diversity measure of an agent's knowledge stock; two knowledge units that used to be distant may now be considered closely related, and vice versa. Indirectly, this would change an agent's realized knowledge preference and subsequently acquisition success rate. For example, an exploitative agent that has accumulated a set of closely related knowledge units in its knowledge stock may suddenly find itself endowed instead with a relatively diverse knowledge stock, such that in continuing to pursue an exploitative strategy, it would prefer new knowledge units that are closely related to any of the knowledge units in its newly diverse knowledge stock. Effectively, it may end up applying a "broad yet deep" approach to knowledge acquisition.

The brief analytical exercise above is intended merely to illustrate some possible consequences of modifying the knowledge map from static to dynamic. The particular manners according to which the parameters of the knowledge map are modified would presumably lead to qualitatively different implications, some of which may be too complex to predict analytically and thus need to be observed experimentally. The relationship between strategy and changing environment is an issue that has always been intriguing and relevant to both scholars and practitioners (e.g., Grant, 2003; Kraatz & Zajac, 2001; Posen & Levinthal, 2012), and so this particular extension of the model is a compelling one.

### 5.2. Density vs. diversity of the knowledge acquisition environment

In the current model, the knowledge acquisition environment is populated with knowledge units that are randomly selected from among the knowledge domains in the knowledge universe (as explained in §3.2). Accordingly, the diversity of the knowledge acquisition environment is measured using density as a proxy rather than directly.

This modeling choice serves two purposes: first, it helps to minimize the number of parameters (and importantly, the number of their combinations) that need to be systematically varied and analyzed, and second, it helps to maintain the focus of this paper on knowledge acquisition strategy rather than on environment parameters. Nevertheless, density is clearly an imperfect proxy for diversity. A knowledge acquisition environment that contains a small volume of every knowledge domain is not easily comparable to one that contains some volume of only a few knowledge domains.

A straightforward extension would ameliorate this problem: A diversity parameter could be added to the model such that the knowledge acquisition environment is described by two distinct parameters: density and diversity. The density parameter would simply determine how many knowledge units are available in the knowledge acquisition environment, whereas the diversity parameter would determine the collective distance between knowledge units in the knowledge acquisition environment.[4]

[4] Note that while density and diversity as described here are distinct parameters, diversity to some extent depends on density: A given level of diversity requires a minimum level of density. For example, if fifty different knowledge domains are to be represented in the knowledge acquisition environment, then the density parameter needs to allow at least fifty knowledge units to be present in the knowledge acquisition environment.

Keeping diversity constant, the primary effect of greater density is that it increases the number of copies of a particular knowledge domain that are available in the knowledge acquisition environment. As such, a dense knowledge acquisition environment essentially facilitates repeated engagement with a particular knowledge domain. A dedicated density parameter is thus likely to interact most noticeably with the magnitude sensitivity parameter; given a positive magnitude sensitivity value, agents of either knowledge acquisition strategy would have greater difficulty acquiring knowledge as the knowledge acquisition environment becomes less dense, and this effect is likely to be worse for the explorative agent when low density is combined with high diversity, because such an agent would attempt to acquire distant knowledge with which it also has minimally engaged. As this brief analytical exercise suggests, the separation of density and diversity parameters from each other could provide a more precise understanding of what drives a particular effect.

Keeping density constant, the primary effect of greater diversity is that it increases the number of distinct knowledge domains that are represented in the knowledge acquisition environment. A diverse knowledge acquisition environment allows the explorative agent to find distant knowledge domains to try to acquire, but of course this may also lower its acquisition success rate. The effect of a dedicated diversity parameter should essentially be very similar to the findings in this paper. Nevertheless, the separation of density and diversity parameters from each other again could help to tell apart the primary and secondary drivers of a particular effect.

### 5.3. Static vs. dynamic knowledge acquisition strategy

Agents in the current model are not allowed to switch strategies during the simulation; they are either exploitative or explorative from start to finish. A natural extension of this feature is thus to allow agents to be able to switch strategies during the simulation, either once or multiple times. Not only would it be an interesting analytical exercise to explore the possibility that there is a formula for an optimal strategy, it would also reflect the reality of strategy-making in practice. Organizations constantly oscillate between (or even simultaneously pursue) exploitative and explorative modes, and so it is of practical interest to understand how such choices can be better managed.

The findings in this paper in general point towards the hazards of pursuing an exclusively explorative strategy, but allowing agents to switch strategy could bring the merits of the explorative strategy into the foreground. One argument for pursuing the explorative strategy is that it could provide organizations with an increasingly diverse knowledge base such that knowledge acquisition becomes easier overall over time. This effect may be more readily observable if agents are allowed to switch to an exploitative strategy once they have acquired a sufficiently diverse knowledge stock. The definition of “sufficiently diverse” here is one that likely has to be determined experimentally.

### 5.4. Conclusion

In conclusion, the full potential of the current model has certainly not been exhaustively explored in this paper. The extensions discussed above are chosen for their immediate relevance, but there are other less obvious ones that are similarly promising, such as the possibility of introducing multi-agent cooperation, which perhaps could be used to study the use of knowledge in teams or alliances, or agent acquisition, which perhaps could be used to study the knowledge combination and recombination aspects of mergers and acquisitions. Evidently, while the current model is presented only in its most basic form, its structural pieces are hopefully proving to be sound enough to allow for the construction of more complex models that are suitable of answering a variety of important research questions in the organizational learning literature.

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**Figure 1: Mechanism of knowledge acquisition**

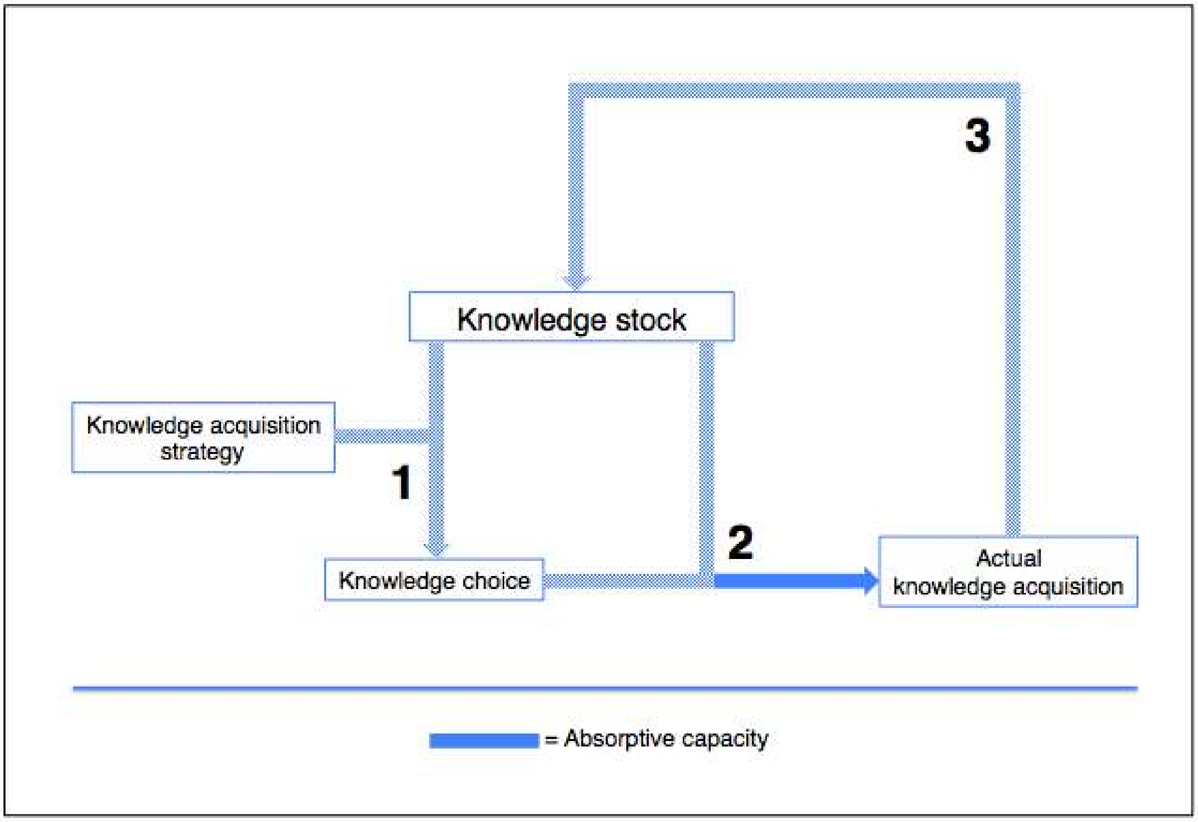


**Figure 2: Model overview**

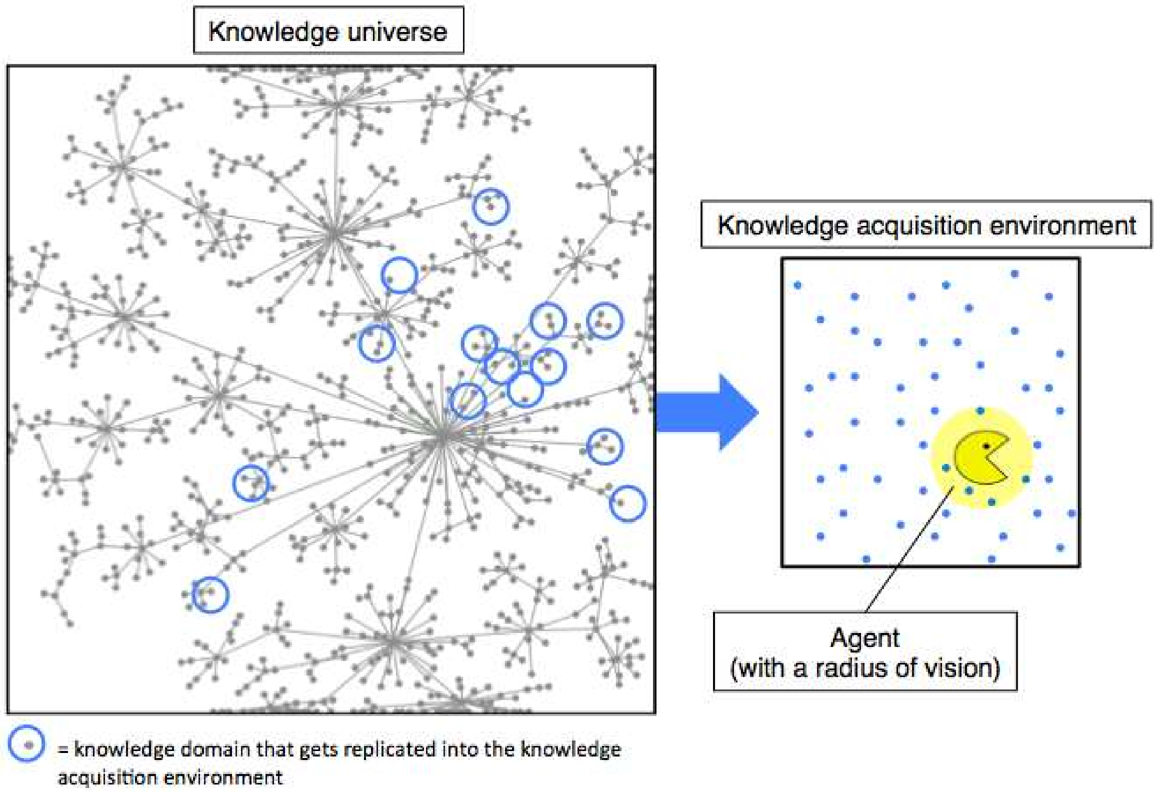


**Figure 3: Distance sensitivity parameter**

**A. Given positive distance sensitivity, the exploitative agent performs better than the explorative agent in terms of acquisition success rate.**

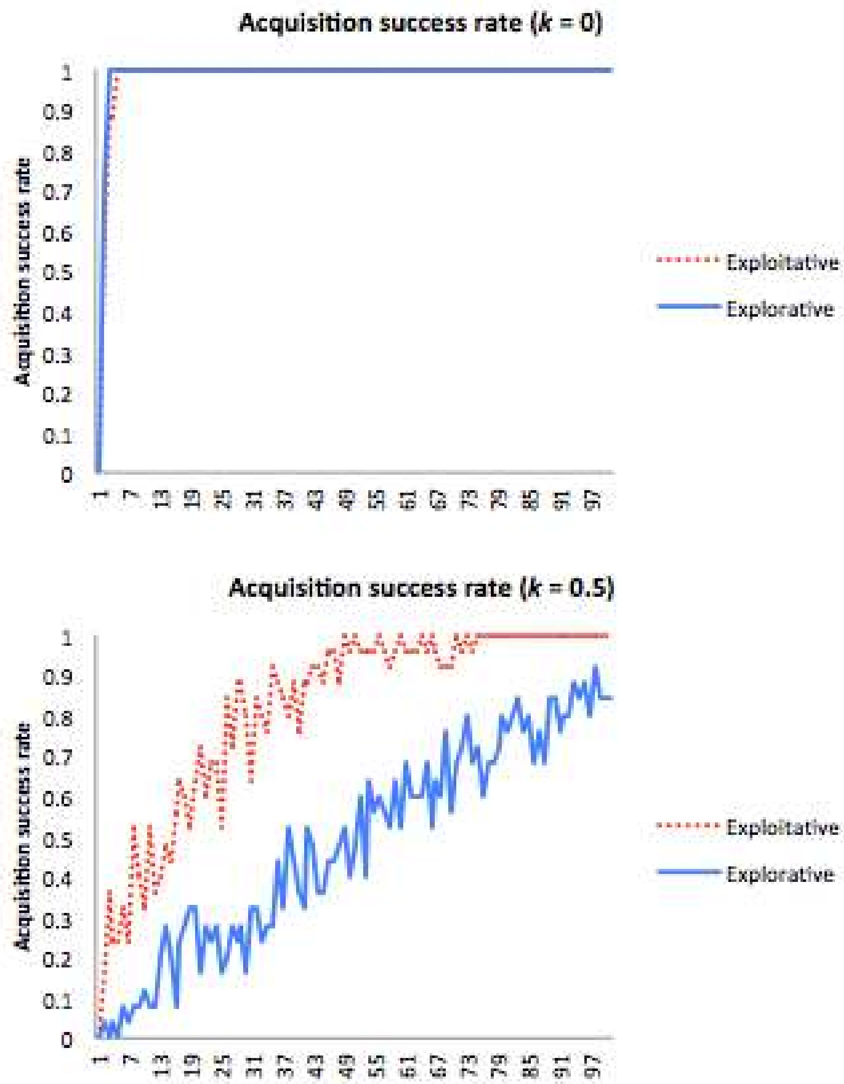


**Figure 3: Distance sensitivity parameter (continued)**

B. **Distance sensitivity can diminish the explorative agent's advantage over the exploitative agent in terms of average path length.**

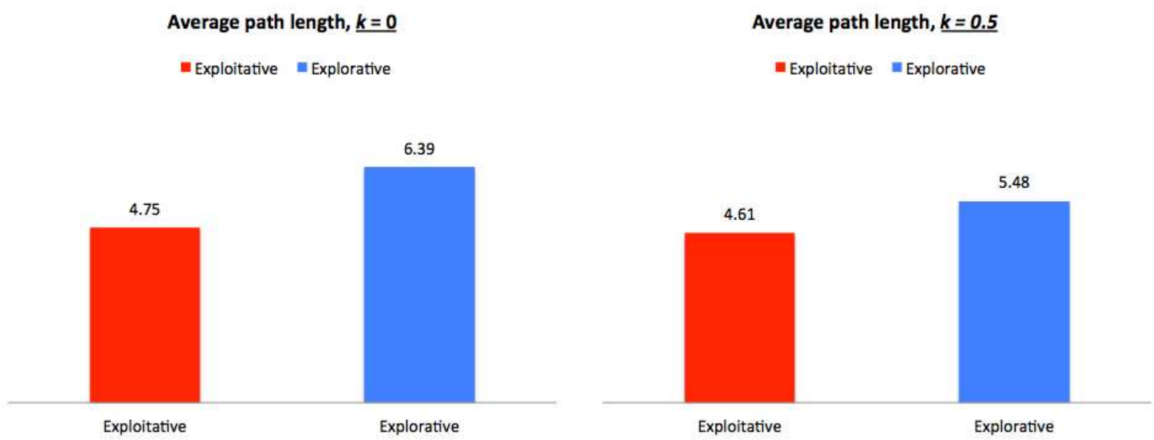
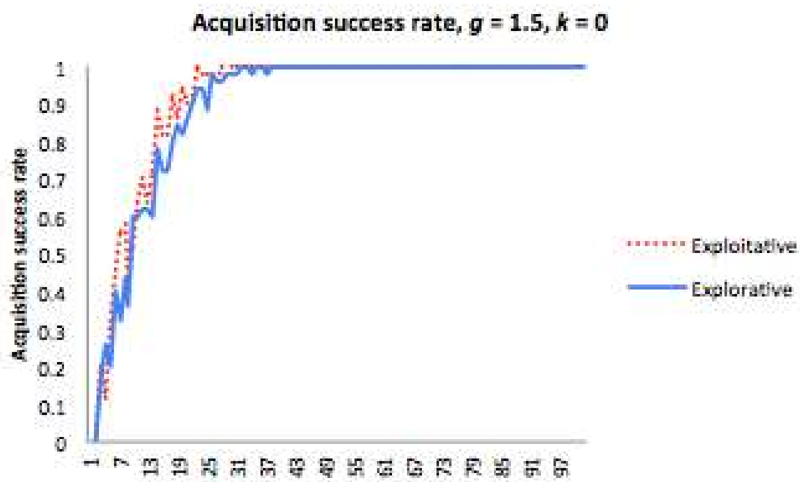


**Figure 4: Magnitude sensitivity parameter**

A. **Magnitude sensitivity *with* distance sensitivity favors the exploitative agent in terms of acquisition success rate.**



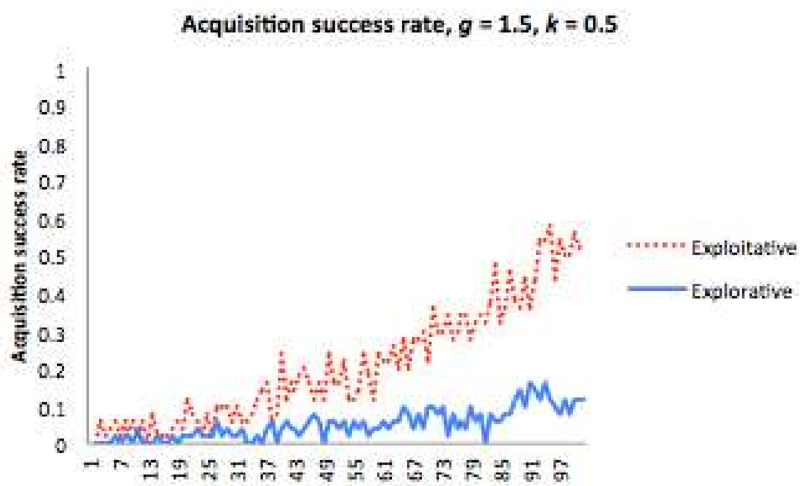
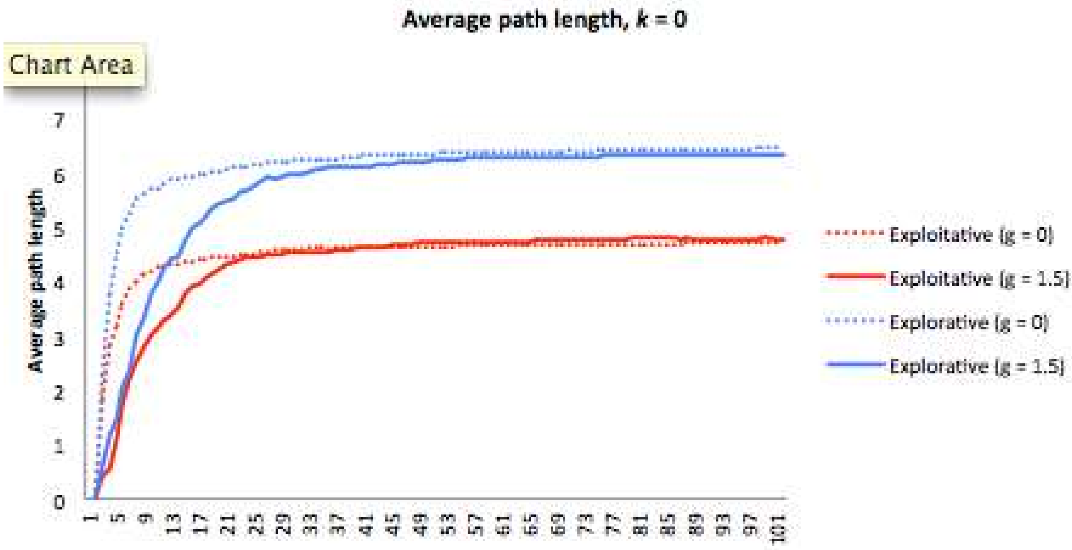



**Figure 4: Magnitude sensitivity parameter (continued)**

**B. Magnitude sensitivity *with* distance sensitivity hurts overall average path length.**



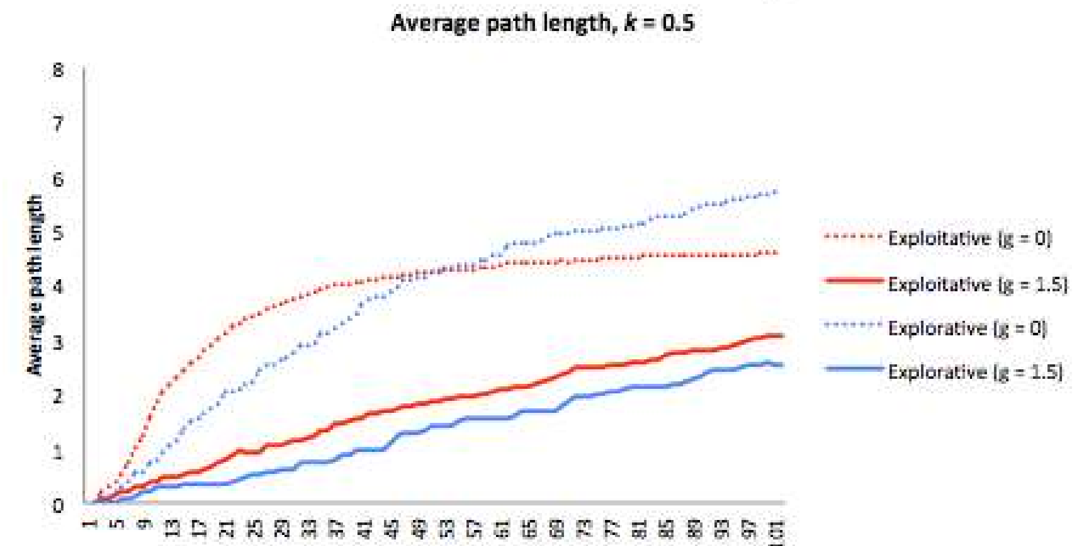
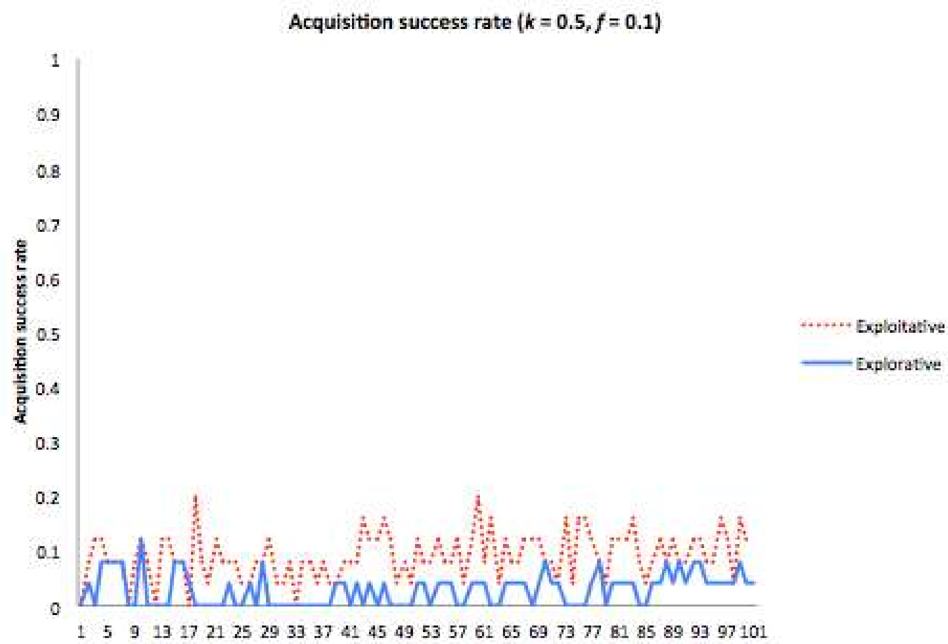



**Figure 5: Age sensitivity parameter**

A. **Age sensitivity amplifies the effect of distance sensitivity in terms of acquisition success rate. (Compare to Figure 3.)**




B. **Age sensitivity amplifies the effect of distance sensitivity in terms of average path length. (Compare to Figure 3.)**