Effective Search in Rugged Performance Landscapes: A Review and Outlook

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ABSTRACT

The creation of novel strategies, the pursuit of entrepreneurial opportunities, and the development of new technologies, capabilities, products or business models all involve solving complex problems that require making a large number of highly interdependent choices. The challenge that complex problems pose to boundedly rational managers—the need to find a high-performing combination of interdependent choices—is akin to identifying a high peak on a rugged performance “landscape” that managers must discover through sequential search.

Building on the NK model that Levinthal (1997) introduced into the management literature, scholars have used simulation methods to construct performance landscapes and examine various aspects of effective search processes. We review this literature to identify common themes and mechanisms that may be relevant in different managerial contexts. Based on a systematic analysis of 71 simulation studies published in leading management journals since 1997, we identify six themes: learning modes, problem decomposition, cognitive representations, temporal dynamics, distributed search, and search under competition. We explain the mechanisms behind the results and map all of the simulation articles to the themes. In addition, we provide an overview of relevant empirical studies, and discuss how empirical and formal work can be fruitfully combined. Our review is of particular relevance for scholars in strategy, entrepreneurship, or innovation who conduct empirical research and apply a process lens. More broadly, we argue that important insights can be gained by linking the notion of search in rugged performance landscapes to practitioner-oriented practices and frameworks, such as lean startup or design thinking.

Keywords: Complexity, performance landscape, search, problem solving, bounded rationality, NK model, simulation
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EFFECTIVE SEARCH IN RUGGED PERFORMANCE LANDSCAPES: A REVIEW AND OUTLOOK

The creation of novel strategies, the pursuit of entrepreneurial opportunities, and the development of new technologies, capabilities, products or business models all involve solving complex problems that require making a large number of highly interdependent choices (Simon, 1962). To successfully address complex problems, managers need to identify combinations of choices that reinforce each other instead of simply selecting the best individual choices. As bounded rationality prevents managers from instantaneously identifying the best or even good combinations, they must engage in sequential search processes (March & Simon, 1958; Simon, 1955) that involve learning about and discovering what is possible and what “works.” For example, Rumelt (2011) describes how Starbucks’ business model was developed through a sequential search process that had an Italian espresso bar as its starting point. The basic challenge posed by complex problems can be illustrated using the metaphor of a “rugged performance landscape” (Levinthal, 1997; Siggelkow, 2002). Each point on the landscape represents one possible combination of choices, while the height of the point represents the performance of that combination. Because interdependencies among choices lead to a rugged landscape with numerous peaks and valleys, they raise the risk that boundedly rational search gets drawn towards a low-performing peak. The managerial challenge is thus to design a search process that helps reach higher peaks while avoiding lower ones (Siggelkow, 2002).

Research on effective search for solutions to complex management problems was stimulated by Levinthal (1997), who introduced a formal model of performance landscapes into the management literature. This so-called NK model, which was originally developed by Stuart Kauffman (Kauffman, 1993; Kauffman & Levin, 1987) in the field of evolutionary biology, allows to computationally “construct” rugged landscapes using the two key parameters of
complex problems: the number of choices (N) and the number of interdependencies between each choice and other choices (K). A stream of research has built on Levinthal (1997), and used computational models and simulations to examine the effectiveness of a broad range of characteristics of search processes in rugged landscapes. A number of these studies have modified and extended the original NK model to examine specific problem structures, such as problems that can be decomposed into modules or problems in which some choices are more important than others. In this paper, we systematically review this literature. In addition, we provide an overview of empirical work that explicitly addresses both the search process and the complexity of the underlying problems.

Our review makes two main contributions. First, we identify common themes among the simulation studies that may be relevant across different empirical contexts, and we explain the general underlying mechanisms that make search processes effective. We identified 71 simulation studies published in leading management journals after Levinthal (1997) that use a variant of the NK model. Based on a systematic analysis of this body of work, we uncovered six main themes along which we structure our review. These themes reflect the “design choices”—different aspects of search processes—that authors have made while working with the NK model: (1) learning modes—the use of experiential learning or imitation to generate better candidate solutions; (2) problem decomposition—fixing some choices or partitioning the problem into subproblems to facilitate effective search; (3) cognitive representations—how insights into the structure of the problem or its solutions can foster search; (4) temporal dynamics—effective sequencing of search efforts and accounting for time constraints; (5) distributed search—how to organize search processes that involve multiple participants; and (6) search under competition—how complexity affects competitive dynamics and leads to heterogeneity among competitors.
SECOND, WE PROVIDE A BASIS FOR BETTER LINKING SIMULATION STUDIES TO EMPIRICAL WORK. RESEARCH ON EFFECTIVELY SEARCHING FOR SOLUTIONS TO COMPLEX MANAGEMENT PROBLEMS HAS BEEN DOMINATED BY COMPUTATIONAL WORK, WHICH IS WELL-SUITED FOR DEVELOPING NEW THEORY (DAVIS, EISENHARDT, & BINGHAM, 2007; HARRISON, LIN, CARROLL, & CARLEY, 2007). ALTHOUGH RELATED EMPIRICAL RESEARCH HAS RECENTLY PICKED UP MOMENTUM, THEORETICAL STUDIES AND EMPIRICAL WORK STILL REMAIN RATHER DISCONNECTED. IN THIS REGARD, WE IDENTIFIED 29 RELEVANT EMPIRICAL ARTICLES THAT FALL INTO ONE OF THREE CATEGORIES: LARGE-SAMPLE QUANTITATIVE TESTS, PROCESS STUDIES (TYPICALLY INDIVIDUAL OR MULTIPLE CASE STUDIES), AND LABORATORY EXPERIMENTS. WE PROVIDE AN OVERVIEW OF THESE ARTICLES, AND DISCUSS HOW EMPIRICAL WORK AND SIMULATION STUDIES CAN BE FRUITFULLY COMBINED.

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Our review is structured as follows. The next section provides a primer on search and complexity, and introduces the rugged-landscapes metaphor as a tool for studying how managers and organizations deal with complex problems. In the third section, we describe how we identified and analyzed relevant simulation-based studies for our review. The fourth section is the core of our review and presents the six themes that we uncovered in the literature. The final section provides an overview of existing empirical research on search and complexity, as well as a discussion of ways to strengthen the links between simulation studies and empirical work.

A PRIMER ON SEARCH AND COMPLEXITY

Bounded Rationality, Complexity, and Search as a Sequential Process

Much of human problem solving can be characterized as a sequential search process (March & Simon, 1958; Simon, 1955) that is directed at identifying solutions and courses of action that are superior to those currently known. Such a search for solutions to complex problems characterizes many management challenges, including the creation of strategies and business models that require trade-offs among the firm’s activities (Porter, 1996; Siggelkow, 2002); the development of new products that combine components and technologies to yield novel or improved functionalities (Fleming & Sorenson, 2001); the management of the “entrepreneurial journey” to achieve product-market fit through systematic experimentation (McMullen & Dimov, 2013; Ries, 2011); the design of entrepreneurial organizations that balance specialization and coordination (Rivkin & Siggelkow, 2003); and the management of projects with multiple conflicting demands (Mihm, Loch, & Huchzermeier, 2003). In addition, various practitioner-oriented practices and frameworks, such as discovery-driven planning (McGrath & MacMillan, 2009), the lean startup (Ries, 2011), or design thinking (Martin, 2009), can be viewed as “recipes” for effective search processes.
Problems must be solved through search instead of optimization because humans are limited in their rationality. Therefore, they are often unable to identify the optimal solution to a given problem (Simon, 1955). However, as Simon (1990) points out, the boundaries of managers’ rationality are not invariant. Instead, they result from the interaction of two factors: (1) limitations in managers’ problem-solving abilities and their approach to solving a given problem, and (2) the demands on problem-solving abilities arising from the nature and structure of the problem. In fact, for problems that are sufficiently simple, the limitations in managers’ abilities may not be binding (e.g., Gode & Sunder, 1993) and managers might be able to easily identify the optimal solution. On the other hand, as complex problems consist of a “large number of parts that interact in a nonsimple way” (Simon, 1962: 468), they defy attempts at optimization (Rivkin, 2000) and, thus, require a sequential search process.

Complex problems pose two fundamental challenges for managers. First, a large number of choices gives rise to a large number of possible combinations, which creates a multi-dimensional “search space.” Second, interdependencies among choices imply that the different combinations vary in terms of their performance or viability (Siggelkow, 2001; Zott & Amit, 2010). Instead of identifying individual choices that are superior, managers must identify sets of choices (combinations) that mutually reinforce each other and yield high performance in certain combinations (Siggelkow, 2002). Along these lines, Porter (1996) notes that the activity systems or business models of successful firms comprise many interdependent choices. Ikea provides an illustration—its choices about standard product design and customer self-service are mutually reinforcing.

Navigating Rugged Performance Landscapes

A useful metaphor for the multi-dimensional search spaces that are spanned by complex problems is that of a “rugged performance landscape” (Levinthal, 1997; Siggelkow, 2001). Each
possible combination of choices is represented by one point on the landscape along a number of “horizontal” dimensions, while the height of each point represents the performance of that combination. The landscape is rugged because interdependencies among choices give rise to peaks characterized by higher performance and valleys in which performance is lower. Ikea’s choices regarding product design and customer service, for instance, might represent a peak on the “furniture” landscape, whereas an alternative peak could be established by combining product design that allows customers to tailor products to their individual tastes with a full-service approach.

A peak represents a choice combination in which performance cannot be improved by changing only one choice. For example, if Ikea were to change only the product-design dimension but retain its choice on the customer-service dimension, the resulting combination would likely reduce performance. Generally, the more interdependent the choices are, the more rugged the landscape becomes and the more peaks it contains. These peaks vary in their height, and most of them are only “local” peaks (local optima). Therefore, solving complex management problems requires identifying high-performing peaks in a rugged performance landscape.

The search for good solutions is difficult in rugged performance landscapes because managers do not initially know which solutions are superior. Therefore, they cannot “jump” directly to a relatively high-performing peak (or even the “global” peak, which is the highest-performing or optimum combination of choices). Instead, better solutions in the performance landscape must be discovered through a sequential search process. In this process, managers start with an initial combination of choices, and seek to identify better solutions by building on existing solutions over time (Nelson & Winter, 1982; Simon, 1955).

The fact that superior solutions are often “distant” in the sense that they require changing more than one choice poses a challenge to the sequential search process. Boundedly rational
decision makers often cannot identify superior solutions that are radically different from the solutions they know. Instead, they generate new solution alternatives through “local” search. That is, they search “in the neighborhood” of their current solution, typically by changing only one dimension of the current solution. If the new solution is superior, the change is implemented; otherwise, it is discarded. This process results in “hill climbing.” Notably, local search that only involves hill climbing typically ends up on a relatively low-performing local peak.

To understand how interdependencies make search difficult, consider the difference between Figure 1A, which represents a “smooth” landscape without interdependencies, and Figure 1B, which represents a rugged landscape. The “starting point” combination in Figure 1A represents a rather poor solution to the problem. However, as interdependencies are absent, hill-climbing local search will lead to the peak regardless of whether the first or the second dimension is changed first. This can be compared with the situation in Figure 1B. From the initial “starting point,” a local search along the first dimension might lead to a “local peak.” To identify the “global peak” (i.e., the best solution in the landscape), one would need to also change the second dimension. The global peak (and local peaks higher than the peak reached by changing the first dimension) could easily be reached by simultaneously changing both dimensions. However, when dimensions can only be changed sequentially, reaching higher peaks becomes much more difficult or even impossible. Thus, in rugged performance landscapes, hill-climbing local search exhibits strong path dependencies and generally moves the organization towards a local peak (Levinthal, 1997). On the other hand, if the problem is simple and the landscape is smooth with only one peak, even local hill climbing will lead to the global peak. Therefore, a search process is effective if it reduces the odds of ending up on a local peak, but its effectiveness also depends on the structure of the problem (this is known as "Simon's scissors"; Simon, 1990). Generally, the
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effectiveness of a search process can be increased by systematically “broadening” the search. A search process that covers a larger part of the landscape makes it possible to identify superior solutions that could not have been reached through a local hill-climbing search process.

The NK Model and Its Variants

To examine the effectiveness of search processes, the literature that builds on the NK model uses formal models and simulations that incorporate both complex problem structures and the characteristics of search processes in a stylized manner (see the glossary in the Appendix for definitions of key terms used in the rugged landscape literature). Other than the continuous performance landscape used for illustration purposes in Figure 1, the performance landscapes in the NK model and its variants are discrete. More specifically, a problem consists of \( N \) binary choices, which result in \( 2^N \) possible combinations of choices. The basic mechanisms of navigating rugged landscapes laid out above also apply to problems with discrete structures.

The performance associated with a certain combination of choices depends on the performance contribution of each individual choice. Problem complexity arises from interdependencies among choices. These interdependencies can be formulated using an “interaction matrix” that, for each pair of choices, specifies whether the performance contribution of one choice depends on the value of another choice (see Rivkin & Siggelkow, 2007, for an overview of different interaction matrices; interaction matrices are also closely related to design structure matrices that are used to map complex product architectures; see Baldwin & Clark, 2000; Eppinger, Whitney, Smith, & Gebala, 1994). In the basic model, the performance contribution of each individual choice depends on the value of \( K \) randomly selected other choices. If \( K = 0 \), all \( N \) decisions are independent. Under these conditions, the landscape is smooth and the global peak can be found through a hill-climbing local search process. At the other extreme, if \( K = N-1 \), the performance contribution of each choice depends on the chosen
value of each of the other choices. This results in a rugged landscape with many peaks of varying
heights and hill-climbing local search will usually end up on a low local peak. Thus, in the basic
variant of the NK model, complexity is understood in terms of its degree. In other words,
problems are more or less complex depending on the number of interdependencies among the
choices.³

Variants of the original NK model represent complexity as specific interdependency patterns
among choices. Two particular problem structures characterize many typical management
problems and have, therefore, been used in several studies. The first are modular problems, which
are typically viewed as subsets of choices that exhibit many interdependencies within each subset
but few interdependencies among the different subsets. Many management problems, ranging
from the development of products that consist of multiple components (Baldwin & Clark, 2000)
to the development of business models that require coordination among functionally specialized
units (Andries, Debackere, & Looy, 2013), exhibit such modular structures. Recent modeling
efforts make an explicit distinction between a modular problem structure, where
interdependencies across modules occur on a single level, and a near-decomposable structure
(Simon, 1962), where interdependencies across modules occur at an aggregate level (see
Levinthal & Workiewicz, 2018, for a discussion).

In the second typical problem structure, some elements or choices are more important than
others. Here, interdependencies often exhibit a hierarchical structure with sequential
interdependence (i.e., a number of core choices affect other choices but not vice versa) or a
structure with asymmetrically influential choices (i.e., some choices are interdependent with
many other choices, others are only interdependent with a few). A key feature of problems with
this structure is that it is important to identify and get the most central choices right. Examples of
such management problems include strategy making (Ghemawat & Levinthal, 2008) or product
development (Baumann & Siggelkow, 2013).

**REVIEWING THE PERFORMANCE LANDSCAPE LITERATURE**

To conduct our review, we identified and analyzed all articles published in major
management journals that incorporated an explicit notion of rugged performance landscapes. As
this stream of research was initiated by Levinthal (1997), the period covered by our review
stretches from 1997 to 2017 (and includes forthcoming papers as of December 31st, 2017). In the
first step, we compiled a list of studies based on our personal overview of what comprises the
“NK literature,” which resulted in 55 simulation studies. To validate and expand this initial set of
studies in a systematic manner, we searched the Web of Science platform and created a list of all
articles that cited Levinthal (1997). This yielded a list of 368 potentially relevant articles. From
this list, we included all articles published in major management journals (using the current FT50
list) or in journals that had published at least three such studies. To cross-validate the list of
articles, we checked all forward citations for certain early studies other than Levinthal (1997) as
well as backward citations for a selected number of recent studies. This resulted in a list of 292
articles.

In the second step, we examined all 292 articles by reading the title, abstract and, if
necessary, the entire text to classify them into three categories: studies using formal/simulation
models (84), empirical studies (143), and conceptual studies (65). Not all simulation models were
based on rugged landscape models, and we excluded those that were not. Moreover, our original
list contained a few articles that were not in the list generated through our Web of Science search.
Our final list of relevant studies therefore contained 71 simulation articles. Table 1 provides an
overview of the number of articles by journal.
We analyzed the simulation studies by examining the key characteristics of the models, and we iteratively developed a coding scheme for characterizing the search processes that were modeled in the papers. Two of the authors independently read through all 71 studies and cross-checked their ratings to ensure inter-rater reliability, while the third author checked the face validity of the coding scheme. This resulted in six themes and 13 sub-themes, which form the basis of our review below. In addition, we placed the studies into the following problem-structure categories: unstructured interdependencies (parameter K represents the degree of complexity, as in the basic NK model), number of choices that decision makers need to get right (as an alternative measure of complexity; see footnote 3), modular interdependencies, nearly-decomposable problems, hierarchical interdependencies, and other approaches. Table 2 lists the different problem structures, themes and sub-themes, and codes. Table 3 provides an overview of the 71 simulation-based articles, including the empirical context of the study, the classification (codes), and the key insight of each article.

In order to obtain an overview of the state of empirical research on search in rugged performance landscapes, we also examined all 143 empirical studies to determine whether they addressed the topic of our review. To be considered, a study had to explicitly address search as a process as well as problem complexity. This was the case for 29 of the empirical articles. We identified three types of relevant empirical articles: large-sample quantitative tests (19), process studies (typically individual or multiple case studies) (7), and experiments (3). 16 of these 29 studies were published since 2012, indicating a growing interest in empirical research on search on rugged landscapes. However, as we used citations of Levinthal (1997) to identify relevant empirical articles, our list may not be comprehensive. Nevertheless, given that Levinthal (1997)
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is the canonical reference, we believe that our study provides a broad indication of the state of
empirical research in this domain.

CHARACTERISTICS OF EFFECTIVE SEARCH PROCESSES

Two Generic Mechanisms that Broaden Search

Before providing our overview of the characteristics of effective search processes, which is
organized around the six themes, we first explain two generic mechanisms through which search
can be broadened beyond the hill-climbing local search process described above. These generic
mechanisms, which help identify superior solutions, operate in many of the studies included in
our review.

One approach is to simultaneously change several choices. This mechanism has been referred
to using labels such as “long jumps” (Levinthal, 1997), “radical innovation” (Chao & Kavadias,
2008), and “pivoting” (Ries, 2011). While even randomly changing several choices will broaden
the search (Levinthal, 1997), a more reliable way to identify superior solutions is to draw from
available insights. One source of insight is learning from others (themes 1—“vicarious learning”
and 6—“heterogeneity”) by observing and imitating their solutions (Rivkin, 2000). Another
source of insight is a coarse representation of the problem space (theme 3), which can be based
on prior related experience (Gavetti & Levinthal, 2000).

As the number of local peaks increases when a problem becomes more complex, the value of
simultaneously changing several choices also increases with problem complexity (Rivkin, 2000).
However, the performance impact of changing multiple choices at the same time depends on the
interdependencies among the choices that are changed and those that are not. If there are such
interdependencies, then changing one set of choices may make otherwise optimal unchanged
choices suboptimal (Siggelkow & Rivkin, 2009). Thus, while simultaneously changing several
choices can help avoid inferior local peaks, subsequent local search may still be necessary to
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further improve the overall solution (theme 1—“experiential learning;” e.g., Gavetti and Levinthal, 2000). This also implies that simultaneously changing several choices is more effective if fewer interdependencies exist between the set of choices that are changed and the set of choices that are not (i.e., if problems have a more modular structure; Baldwin and Clark (2000); see theme 2—“partitioning the problem”).

A second approach is to sequentially broaden the search, which provides access to more distant solutions despite only changing one choice at a time. Such a local search process differs from hill climbing in that it lets managers make “mistakes” and sometimes select alternatives that reduce performance compared to the current set of choices (i.e., search may sometimes proceed “downhill”). Such mistakes can occur, for example, when managers cannot precisely evaluate a solution’s performance (e.g., due to noise or an inability to see performance implications; Jain and Kogut, 2014) or during the implementation of an alternative (e.g., when routines delay implementation of superior solutions; Yi et al., 2016). The mistakes induced by effective search processes are often not completely random because they help managers go downhill to avoid lower local peaks, while providing stability around higher local peaks. Generally, mistakes can be useful when they serve as stepping stones that help identify superior solutions at a later point (i.e., what is optimal at one point in time may not be optimal at a later point in time; see also theme 4—“temporal dynamics”). A classic example of such a mistake is the weak glue accidentally discovered by a scientist at 3M, which led to the development of Post-It Notes. While initially worse than the existing solution, the weak glue became the foundation of a multi-billion dollar business when other choices were subsequently changed. The mechanisms that induce mistakes may appear to be “foolish” (March, 2006) because they often increase rather than decrease the boundedness of rationality. For example, as we show below, deliberately imposing limits on the imitation of superior solutions (theme 1—“vicarious learning”), restricting the search domain
(themes 1 and 2—“constraints”), or allowing for imperfect coordination in distributed search processes (theme 5—“coupled search”) may, in fact, ultimately lead to better solutions.

**Theme 1: Learning Modes**

To solve a problem, a search process must identify and evaluate possible solutions. Two approaches, which constitute two alternative modes of learning, are typically modeled: experimentation as a form of experiential learning and imitation as a form of vicarious learning (Huber, 1991).

**Experiential learning.** Local search can be seen as a series of experiments that involve changing only one choice at a time and learning from the resulting performance feedback. Thus, for a problem that consists of N decisions, N different experiments can be performed at a given time. Different ways of identifying and evaluating local alternatives have been modeled, which range from randomly changing one choice to examining multiple or even all N alternatives and selecting the best (Rivkin & Siggelkow, 2003). In addition, other design choices (e.g., restricting the set of choices that can be changed; see theme 2; or dividing the work of identifying and selecting alternatives between subordinates and a manager, see theme 5) can affect the local alternative that is identified or selected.

While many authors have touted the benefits of systematic experimentation (Farjoun, 2008; Mosakowski, 1997; Thomke, 1998), rugged landscape models offer the basic insight that as long as experimentation is local and fails to consider interdependencies, it will likely only lead to a low local peak. On the other hand, local experimentation can lead to identification of superior alternatives when it is coupled with other characteristics of search processes. For example, local experimentation helps fill gaps when insights from prior experience (Gavetti & Levinthal, 2000) or from imitating others (Posen & Martignoni, 2018) provide only a rough indication of the choices that constitute a superior alternative, or when the most important choices have been fixed.
but the details still need to be worked out (Ghemawat & Levinthal, 2008). However, local experimentation may also compensate for and, thereby, mask poor higher-level choices (Siggelkow & Rivkin, 2009).

**Vicarious learning and imitation.** Vicarious learning relies on observing and imitating the solutions found by others. Imitation is a substitute for experimentation in the sense that it allows for better decision making without the need for an experiential learning process. Yet, as Rivkin (2000) shows, complex problems make it difficult to rely on imitation as a substitute for experimentation. This is because even small errors in imitation may lead to significant performance penalties. Moreover, imitation may be detrimental when only some choices are imitated while idiosyncratic interdependencies between the imitated choices and one’s other choices are ignored (Almirall & Casadesus-Masanell, 2010; Csaszar & Siggelkow, 2010).

Imitation also serves as a complement to experiential learning in the sense that the latter can improve upon the alternatives identified by the former. This can occur through local search to “fill gaps,” as noted above. It can also occur by generating potentially useful variation through novel combinations that enable the subsequent discovery of better solutions (Csaszar & Siggelkow, 2010; Posen & Martignoni, 2018). Counter to what intuition might suggest, this generative effect of imitation is most beneficial when there is a limit to how much and how correctly a firm can imitate. In other words, imitating too much or imitating with too much precision precludes the potential for subsequent improvements through local search (Csaszar & Siggelkow, 2010; Lazer & Friedman, 2007). This echoes March’s (1991) argument for sustaining diversity in learning systems.

The mechanisms that allow imitation to act as both a substitute and a complement to experimentation also apply to firm-internal replication and, as such, suggest boundary conditions to approaches that rely on replication (Winter & Szulanski, 2001). However, Rivkin (2001)
shows that if internal replication is less error-prone than external imitation, then replicators have an advantage over external imitators at intermediate levels of complexity.

**Theme 2: Problem Decomposition**

A second general approach to increasing search effectiveness is to decompose the overall problem. Simulation studies have considered two types of decomposition: reducing the scope of the problem by restricting the set of choices that can be changed and partitioning the problem into “sub-problems” that comprise subsets of choices.

**Restricting the set of choices.** The literature offers multiple reasons for why firms might only search a subset of choices while keeping the other choices fixed. Among these are strategic commitments to certain choices (Ghemawat & Levinthal, 2008), corporate level-strategies that restrict business-level strategic choices (Caldart & Ricart, 2007), the limits of attention (Gavetti & Levinthal, 2000; Posen & Martignoni, 2018), or a lack of plasticity (Levinthal & Marino, 2015). As these studies show, keeping certain choices fixed may, in fact, lead to superior outcomes when compared to searching across all choices. This is because when some choices are more important than others, making those choices first and committing to maintaining them can improve the effectiveness of search (Baumann & Siggelkow, 2013; Ghemawat & Levinthal, 2008). In other words for complex problems, strategic commitment to the most important choices often has a beneficial effect, at least if the selected set of choices has been correctly identified (Ghemawat & Levinthal, 2008; Siggelkow & Rivkin, 2009; Welter & Kim, 2018). In addition, when attention is limited and managers cannot simultaneously consider all choices, it pays to restrict the set of choices (Gavetti & Levinthal, 2000; Posen & Martignoni, 2018).

**Partitioning the problem.** Partitioning a problem into sub-problems is a prerequisite for reaping the benefits of the division of labor and specialization. Interdependencies among choices affect whether divided or integrated search is superior (Levinthal & Warglien, 1999; this is also
the premise of Nickerson & Zenger’s (2004) “problem-solving” perspective). More specifically, interdependencies among choices that are part of different sub-problems may lead to coordination problems (Rivkin & Siggelkow, 2003). A modular problem structure helps minimize such coordination problems (Baldwin & Clark, 2000; Simon, 1962), at least to the extent that the partitioning corresponds to the true modular problem structure. In this regard, Ethiraj and Levinthal (2004b) show that it is better to decompose a problem into too few modules than too many.

Partitioning the problem also allows organizations to effectively recombine and adopt complete modules made available by others. As Almirall and Casadesus-Masanell (2010) show, an “open innovation” approach of adopting modules developed by others rather than searching by oneself is beneficial when complexity is low. On the other hand, Ethiraj, Levinthal, and Roy (2008) identify a trade-off: although modular systems can help reap the benefits of recombination, they also make imitation easier. This may reduce heterogeneity among organizations and keep innovators from appropriating the benefits of their innovations. Finally, partitioning allows for a focus on the performance of individual modules. As Podolny (2018) shows, imposing a minimum performance requirement on individual choices or modules makes managers more selective. Such selectiveness broadens the search process and can, therefore, lead to better outcomes.

**Theme 3: Cognitive Representations**

Cognitive representations capture particular aspects of the actual problem space (Levinthal, 2011; Simon, 1955) and can improve the effectiveness of search in two ways: by providing coarse insights into potentially superior solutions and by offering an understanding of the structural characteristics of the problem. In addition, representations can change during the actual search process.


**Insights into superior solutions.** Representations have been modeled as coarse, lower-dimensional approximations of the true problem structure (Gavetti & Levinthal, 2000) or as portfolios of useful solutions to similar problems (“analogies;” Gavetti, Levinthal, & Rivkin, 2005). Coarse representations are effective because they allow for “offline” evaluations of solutions, which means that superior solutions can be identified without testing them through experimentation as a form of “online” evaluation (Gavetti & Levinthal, 2000). In particular, coarse representations restrict the search space to solutions that have higher expected performance. They establish a superior starting point for subsequent experiential search processes to fill the gaps (Gavetti & Levinthal, 2000; Sommer & Loch, 2004). As Gavetti et al. (2005) show, coarse insights are most effective when the problem cannot be easily modularized, and it is better to have a broad array of coarse insights from similar problems than to have more fine-grained insights into the solution to a particular similar problem. A coarse representation also allows for selective intervention when delegated search efforts lead to a suboptimal solution (Gavetti, 2005).

**Insights into the problem structure.** Representations of the underlying problem structure facilitate problem decomposition. For example, an understanding of whether interdependencies are patterned in a modular way allows for more effective partitioning and division of labor (Ethiraj & Levinthal, 2004b). Similarly, identifying the choices that are more important allows for search efforts to be focused on certain areas (Baumann & Siggelkow, 2013; Ghemawat & Levinthal, 2008). Finally, an understanding of interdependencies enables evaluation of the contributions of each particular choice, which in turn allows for prioritization of the choices that will make the most difference (Solow, Vairaktarakis, Piderit, & Tsai, 2002).

Together, these results imply that when an organization faces a complex problem, the presence of a central coordinator or “strategist” with insights into the problem structure allows
for more effective search. This finding is particularly relevant for the stream of literature on strategy and corporate entrepreneurship that views strategy as “guided evolution” (Foss, 2003; Levinthal, 2017; Lovas & Ghoshal, 2000). In fact, while insights into superior solutions allow for selective intervention, insights into the problem structure allow for a better organization of search efforts without requiring any insight into superior solutions.

**Changing representation.** Several simulation studies incorporate changes in representations as part of the search process (e.g., Gavetti & Levinthal, 2000; Siggelkow & Rivkin, 2009). They show that changing a representation can improve search effectiveness, especially when current performance is relatively low (Gavetti & Levinthal, 2000) and when problems are more complex (Csaszar & Levinthal, 2016). Changes in representation are typically modeled as higher-order experimentation that broadens search but does not rely on any superior insights. An exception is Knudsen and Srikanth (2014), who model a process of updating the representation by using search feedback, which informs managers’ understanding of the true problem structure and, thus, redirects the search to attractive parts of the landscape.

**Theme 4: Temporal Dynamics**

As search processes unfold over time, searchers may benefit from sequencing their search efforts. In addition, in the presence of time constraints, the speed of performance improvements may matter more than long-run performance potential. These factors can affect which search characteristics may be considered most effective.

**Sequencing.** In a sequential search process, what is learned at one point in time affects what can be learned at a later point in time. The general challenge in this process is ensuring stability around the good choices that are identified while the search for further improvements continues (Rivkin & Siggelkow, 2003). As a consequence, quickly identifying good choices and constraining subsequent search efforts to filling the gaps improves search effectiveness.
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(Ghemawat & Levinthal, 2008; Welter & Kim, 2018), as does the ability to prioritize choices (Solow et al., 2002). More generally, as the benefits of simultaneously changing several choices decrease over time or with the number of search trials (Kauffman, Lobo & Macready, 2000; Levinthal, 1997), sequencing by switching from characteristics that induce broad search to characteristics that rely on hill-climbing local search increases the effectiveness of the search process. In this vein, Siggelkow and Levinthal (2003) show that a switch from a decentralized organization to a centralized organization outperforms both centralized and decentralized search. Similarly, Baumann and Siggelkow (2013) find that initially restricting the number of choices that are considered and expanding the search domain over time is superior to considering all choices from the start.

**Time constraints.** Characteristics that initially lead to steep improvements may be inferior in the long run and vice versa (Levinthal & Posen, 2007). The relevant time horizon may therefore affect the characteristics that should be considered effective. When time is limited, search strategies that allow for “quick wins” (i.e., quickly achieve high performance) and that reduce the likelihood of mistakes are superior. For example, Csaszar and Levinthal (2016) demonstrate that, when faced with a time constraint, it is better to stick to the original problem representation and find the best possible solution within that representation than to search for a better representation. When search efforts are distributed, coordination allows for faster initial improvements (Lazer & Friedman, 2007; Mihm et al., 2003). Baumann and Siggelkow (2013) show that, when faced with time constraints, it is better to quickly expand the search domain. They also show that relaxing constraints at fixed intervals is one way to balance the trade-off between steep initial improvements and potential long-term performance. Generally, time constraints have an effect similar to search costs—they impose constraints on the number of available sequential trials,
thereby giving an advantage to search characteristics that quickly achieve high performance (Uotila, Keil, & Maula, 2017).

**Theme 5: Distributed Search**

Search efforts can be distributed among organizations, organizational units, or individuals in two basic ways. In “parallel search,” multiple agents search simultaneously for better solutions to the same problem. In “coupled search,” the problem is decomposed and a subset of choices is allocated to each of two or more agents that are coupled by interdependencies between them.

**Parallel search.** In many contexts, an alternative to broadening the scope of search is to increase the number of parallel search “trials.” Such trials can be seen as a portfolio of projects (Sommer & Loch, 2004), the parallel search efforts of a number of individuals (Kavadias & Sommer, 2009), or a portfolio of organizational practices (Levinthal & Marino, 2015). Parallel search is also typical in situations in which multiple organizations seek to identify solutions to the same complex problem. Parallel search across the same problem space provides variation that can be used as an input to improve a particular solution or to select the best solution from a portfolio of solutions (Sommer & Loch, 2004). In this regard, we focus on ways to reap the benefits of parallel search when searchers cooperate. We review the competitive aspects of parallel search under theme 6.

We have already noted that the benefits of vicarious learning stem not only from taking advantage of superior solutions but also from being able to improve upon the solutions generated by others. Simulations show a trade-off between these two effects—imitation leads to convergence on the best available solution at that time, but it reduces variation among parallel searchers and, thereby, does not allow the organization to enjoy the benefits from the generative effect of vicarious learning (March, 1991; Posen & Martignoni, 2018). As a consequence, various “frictions” that limit the extent of vicarious learning and, thereby, sustain variation among
parallel searchers can be beneficial. These frictions may include partial isolation, such as limiting communication and influence (Fang et al., 2010; Lazer & Friedman, 2007; Posen, Lee & Yi, 2013); cognitive frictions, such as limiting the breadth of imitation, the number of choices to copy (Csaszar & Siggelkow, 2010), or the observability and accuracy of imitation (Rivkin, 2000); and economic frictions, such as costs of imitation (Uotila et al., 2017). When complexity is high, it may even be better to completely avoid imitation of others, and instead engage in a number of isolated parallel trials and select the best solution (Kavadias & Sommer, 2009).

Coupled search. When a complex problem is decomposed into sub-problems and the “labor” of searching for good solutions is divided among multiple searchers, interdependencies among the choices allocated to these searchers often remain. This leads to coupled search processes, which induce the classic trade-off between specialization and integration (Lawrence & Lorsch, 1967; Puranam, Alexy, & Reitzig, 2014). This trade-off exists both within organizations and among multiple organizations that search for solutions to complementary but interdependent problems (Almirall & Casadesus-Masanell, 2010).

In situations characterized by complexity, coupled search processes can entail what Rivkin and Siggelkow (2002) term sticking points, which arise when searches get stuck on configurations that are not local peaks on the landscape. In other words, even when hill-climbing local search would allow for an improved solution from the perspective of the organization as a whole, the individual searchers in a coupled search process may not view that solution as an improvement. Conversely, when interdependencies among individual searchers exist, broadening search at the individual level may reduce the search breadth at the organizational level (Siggelkow & Rivkin, 2006). Consequently, to be effective, coupled search may benefit from central (or hierarchical) coordination by a CEO or a superior (Marengo & Pasquali, 2012). However, there is a trade-off (Rivkin & Siggelkow, 2003): while hierarchical coordination
provides benefits by preventing a move away from sets of good choices that are interdependent across individual searchers, a lack of coordination may help in identification of those choices in the first place.

Work that examines factors that affect this trade-off shows that the benefits of centralized coordination are stronger when individual units are able to identify better solutions for their respective sets of choices (Rivkin & Siggelkow, 2003), when the managers of the individual units are rewarded for organization-wide performance (Rivkin & Siggelkow, 2003), and when environmental turbulence renders the individual units’ accumulated knowledge useless (Siggelkow & Rivkin, 2005). Ethiraj and Levinthal (2009) demonstrate that when there are multiple conflicting goals, search effectiveness can be improved by focusing on a single overall goal and, potentially, switching to a different goal over the course of the search process, or by allowing different units to pursue different goals. Generally, lower problem complexity or higher modularity increase the benefits of dividing search efforts (Aggarwal, Siggelkow, & Singh, 2011; Almirall & Casadesus-Masanell, 2010) and the benefits of encouraging individual units to engage in more distant search (Siggelkow & Rivkin, 2006). Dosi, Levinthal, and Marengo (2003) show that better problem decomposition makes decentralized evaluation more valuable. Ethiraj and Levinthal (2004a) show that problems in which some choices are more important than others allow for more effective decomposition and division of search efforts. These studies not only show the benefits of a central coordinator, but point to particular design choices that increase the effectiveness of search efforts while acknowledging the central trade-off between resolving the coordination problem and limiting the breadth of search.

**Theme 6: Search under Competition**

Finally, a number of studies consider the effects of search when the searching organizations are in a competitive relationship. These studies address two aspects of competition: how
complexity affects heterogeneity among a set of competing organizations and how certain characteristics of search processes may give some organizations an advantage as competition unfolds over time.

**Heterogeneity.** Complexity acts both as a source of heterogeneity and as a factor that sustains heterogeneity among a set of competing organizations. As such, it affects opportunities for creating and sustaining competitive advantage (Barney, 1991; Porter & Siggelkow, 2008). Both the problem structure and the characteristics of search processes affect heterogeneity among competitors that are searching the same rugged landscape. In general, search processes will endogenously reduce initial heterogeneity among a set of competitors over time (Levinthal, 1997), especially when they search broadly or they imitate each other (Posen et al., 2013). On the other hand, the degree of heterogeneity among competitors is also conditioned by the degree of complexity (Rivkin & Siggelkow, 2007), and it depends on whether there are multiple performance dimensions and the correlations among them (Adner, Csaszar, & Zemsky, 2014). As complexity affects heterogeneity among competing firms, work that couples models of rugged performance landscapes with industrial organization models of competition (e.g., Cournot) shows that complexity affects the degree of rivalry and the distribution of profits within an industry (Lenox, Rockart, & Lewin, 2006, 2007).

Not only is heterogeneity a consequence of complexity but complexity also sustains heterogeneity because it constitutes an isolating mechanism (Rumelt, 1984). More specifically, interdependencies among choices act as a barrier to low performers’ attempts to catch up with high performers because they lead to a significant discount when small errors are made (Knudsen, Levinthal, & Winter, 2014; Rivkin, 2000), and when interdependencies between imitated and non-imitated choices are ignored. On the other hand, imitation is more effective at
reducing heterogeneity if the problem has a modular structure and complete modules can be adopted (Ethiraj et al., 2008).

**Competitive dynamics.** Competitive dynamics among organizations that search the same complex landscape in parallel constitute a situation of “co-evolution” (McKelvey, 1999). In this context, differences in the characteristics of organizations’ search processes may affect their relative performance. This has been modeled in two ways based on the type of interdependency in performance outcomes among competitors. First, when the relative performance of parallel search efforts matters, performance outcomes may be indirectly interdependent (e.g., Chang & Harrington, 2003). Relative performance may affect survival when, at any point in time, low performers have an increased likelihood of being selected out (e.g., Levinthal, 1997). In such cases, search strategies with greater initial variance reduce the likelihood of survival (Levinthal & Posen, 2007). Second, performance outcomes may be directly interdependent if the choices of one organization affect the performance outcomes of another organization. For example, Ganco and Agarwal (2009) show that when organizations can learn from each other, those that are exposed to lower levels of complexity have a late-mover advantage that is not available to highly complex organizations. Gavetti, Helfat, and Marengo (2017) demonstrate that while the ability to affect (or “shape”) others’ performance outcomes can be a source of advantage, overly extensive shaping may backfire.

**LINKING SIMULATIONS AND EMPIRICAL RESEARCH**

The simulation studies reviewed above provide theoretical insights into the characteristics of effective search. To date, however, this theoretical work has only been incidentally complemented by empirical research. As such, theoretical and empirical work are rather disconnected. In the following, we provide an overview of the three types of studies that have empirically examined search processes (i.e., large-sample quantitative tests, process studies, and
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experiments) as well as their outcomes and we develop a brief outlook for future research for each of them. In addition, we discuss how empirical insights may inform future theoretical work. Note that we only include empirical work that explicitly accounts for both a complex problem structure and a search process aimed at identifying superior solutions to that problem.9

Large-sample quantitative Tests

Overview. The simulation studies reviewed above make a number of testable predictions about how the structure of complex problems and various characteristics of search processes affect outcomes such as performance. In any empirical test of these predictions, one must observe, for a sufficiently large sample, the outcome of a search process as the dependent variable as well as the problem structure and characteristics of that search process as the independent variables.

Several studies that incorporate problem structure as an independent variable build on the complexity measures based on the N and K parameters introduced by Fleming and Sorensen (2001) and use patent data (e.g., Alnuaimi & George, 2016; Fleming & Sorensen, 2004; Ganco, 2013, 2017). In a corporate-strategy context, Zhou (2013) measures complexity as the number of business units that provide inputs to each other (K) relative to all business units (N) within a multi-business firm. Some studies in innovation contexts measure problem complexity simply as problem difficulty (e.g., Macher, 2006), which means that these studies ignore interdependencies and specific problem structures. In other studies, scholars rely on managerial perceptions to measure complexity (e.g., Lenox, Rockart, & Lewin, 2010; Sommer, Loch, & Dong, 2009). Zhou (2013) includes a measure of problem decomposability as an indication of modular problem structure (Ethiraj & Levinthal, 2004b; Simon, 1962).

The studies by Fleming and Sorenson (2001), Ganco (2017), Lenox et al. (2010), and Lee and Alnahedh (2016) provide broad support for some of the fundamental predictions about how
problem complexity affects the outcomes of search processes. Fleming and Sorenson (2001) examine patent citations as an outcome based on knowledge combinations as inputs. Lenox et al. (2010) test the predictions from Lenox et al. (2006, 2007) about the distribution of profits in industries as a function of industry complexity. In addition, a number of studies test predictions about how complexity affects other outcomes, such as organizational design in a multi-business firm (Zhou, 2013) or cost misestimations in offshoring projects (Larsen, Manning, & Pedersen, 2013). Frenken (2000) builds on the NK model to study the organization of innovation networks in the airline industry, while Frenken and Nuvolari (2004) examine the distribution of product designs in the early steam-engine industry.

A few studies examine whether cognitive representations improve the effectiveness of the search process (theme 3). Fleming and Sorenson (2004) show that, among scientists, search leads to better patents when guided by a representation of the underlying problem space (Gavetti & Levinthal, 2000). However, Mastrogiorgio and Gilsing (2016) do not find support for their hypothesis that experience with similar problems (which they call “analogical ability”; Gavetti et al., 2005) allows scientists to better deal with complexity. In an entrepreneurship context, Sommer et al. (2009) corroborate Sommer and Loch's (2004) predictions by comparing the effectiveness of parallel trials and trial-and-error learning in augmenting venture performance among a sample of Chinese start-ups (themes 1 and 5). Finally, in the context of technology strategy, Caner, Cohen, and Pil (2017) show that knowledge acquired from alliance partners (Posen et al., 2013) is useful in redirecting search efforts to superior outcomes (theme 1—“vicarious learning”).

Opportunities. Most of the predictions from simulation-based work on search and complex problems have yet to be tested empirically. Ultimately, while some ingenuity may be required to develop appropriate measures for problem structure and complexity as well as for the
characteristics of effective search, there are ample opportunities to subject the theoretical insights reviewed above to empirical tests. For example, in relation to theme 4, researchers could examine the intertemporal trade-off between steep improvements and long-term performance as well as sequencing strategies in new product development (Baumann & Siggelkow, 2013).

Case Studies of Search Processes

Overview. A second set of studies examines search processes that unfold over time. A number of scholars build on the idea of search in a complex problem space to examine how an organizational system of activities (or a “business model”) comes into existence and evolves over time, including Siggelkow (2002), who offers a case study on Vanguard; Gavetti and Rivkin (2007), who study Lycos; and Gavetti and Menon (2016), who examine Merrill Lynch. Maggitti, Smith, and Katila (2013) apply a complexity lens to examine the process of invention over time. Cattani, Dunbar, and Shapira (2017) develop an argument that a commitment to particular choices (remaining close to the original peak, theme 2—“constraints”) enabled Steinway & Sons to differentiate itself when the rest of the industry moved to another peak (theme 6—“heterogeneity”). Building on the distinction between local and distant search to analyze the search processes of six technology start-ups, Andries et al. (2013) find that commitment (theme 2—“constraints”) provides short-run benefits, while simultaneous experimentation (theme 5—“parallel search”) is better for long-term performance. Finally, Berends, Smits, Reymen, and Podoynitsyna (2016) analyze the search processes of four corporate ventures, and identify patterns in the ways that managers switch from experiential to cognitive search and vice versa (theme 3).

However, while the studies summarized above provide deep insights into actual search processes, they are often only casually linked with the modeling literature, and they typically only cite one or a few of the original studies, such as Levinthal (1997), Gavetti and Levinthal
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(2000), or Rivkin (2000). For example, while Berends et al. (2016) explicitly build on insights from early simulation studies, especially Gavetti and Levinthal's (2000) notion of cognitive search, they do not link their findings to insights from subsequent modeling efforts. In fact, the patterns of switching between experiential and cognitive search identified by Berends et al. (2016) resemble Csaszar and Levinthal’s (2016) model of two-level search. One exception in this regard is the study by Dattée and Barlow (2017), which uses insights from a case study to critically examine and qualify the results from earlier simulation studies.

Opportunities. As most of the theoretical insights reviewed above have rarely informed empirical work, there are substantial opportunities for cross-fertilization between empirical process studies and simulation-based models. However, to capture these opportunities, researchers may need to better understand the extant theoretical work—an objective to which this review seeks to contribute. In addition, while future research can add to the studies summarized above by examining specific characteristics of search, scholars could also develop more general process models of search that are informed by simulation results. In fact, Maggitti et al. (2013) argue that established process models of search typically do not account for the fact that the search space is complex. In addition, given that complexity induces an intertemporal trade-off, researchers could fruitfully examine how this trade-off materializes in actual search processes. For example, researchers could empirically analyze the role of strategy (in terms of constraining choices, theme 2) in the search processes that entrepreneurs use to identify superior business models. Relevant questions in this regard include: Which choices are or should be fixed, and at what point (theme 4—“temporal dynamics”)? What prompts entrepreneurs to fix choices? What are the performance implications of fixing certain choices and not others as a function of the problem structure faced by entrepreneurs?

Experiments

The general idea behind using experiments in connection with simulation studies is analogous to, for example, behavioral game theory (Camerer, 2003)—a stylized theoretical model is translated into an empirical setup to examine the extent to which individuals or groups behave as predicted by the model. Similar to experimental game-theory studies, actual search behavior in a complex problem space may deviate from the results obtained in simulation studies. For example, in all three experimental studies mentioned above, subjects often searched more broadly or were less likely to lock in on an inferior solution early on, which suggests a behavioral tendency to go beyond myopic, hill-climbing local search.

Opportunities. Experimental testing of the predictions of simulation models is important because it allows for examination of the behavioral assumptions behind the models. As experimental studies that examine search processes in complex problem spaces are rare, there is a substantial opportunity to derive new insights from further studies. Moreover, the results of experiments allow for construction of more realistic models of search behavior. To capture these opportunities, researchers will need to move beyond models that are mainly metaphorical (i.e., based on stylized empirical facts) towards messier, empirically informed models that may have higher predictive power (Hofman, Sharma, & Watts, 2017).

Additional Simulation Studies based on Empirical Observations
There are ample opportunities for future conceptual or theoretical work that builds on and extends the NK model. For instance, one may introduce a model in which the interdependence structure is not exogenously given but can be changed by managers (Levinthal & Warglien, 1999). However, simulation studies are often motivated by conceptual or theoretical concerns—they are not necessarily inspired by empirical observations of actual search processes. Thus, while our review may help identify additional characteristics of search processes that can be fruitfully examined in future theoretical work, we wish to highlight three ways in which empirical observations could be translated into simulation studies.

First, substantial empirical evidence indicates that individual differences among managers matter for organizational-level outcomes (Felin, Foss, & Ployhart, 2015). However, few simulation studies (Rivkin & Siggelkow, 2003) explicitly incorporate individual managerial characteristics. Simulation studies could examine how search processes could be organized to best match these individual characteristics (e.g., addressing themes 3 and 5—partitioning a problem to account for particular expertise or the lack thereof, and determining the best allocation of roles to individuals). Second, anecdotal evidence suggests that search processes are sometimes more forward-looking than admitted by previous model-based work. In addition to being based on superior insight via a coarse cognitive representation (Gavetti, 2012; Gavetti & Levinthal, 2000) such forward-looking search may be “theory-driven” (Felin & Zenger, 2009, 2017). Specifically, managerial theories may provide higher-order direction to search efforts (theme 3—“structural insights”) as well as enable sequencing (sequentially partitioning the problem and search across modules; themes 2 and 4). Third, the practices for systematic experimentation and problem-solving that have recently become popular (e.g., the lean startup or design thinking; Martin, 2009; Ries, 2011) could be translated into simulation models in order to examine their effectiveness as well as their boundary conditions (see Contigiani & Levinthal, 2018).
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CONCLUSIONS

When firms and managers create novel strategies, pursue entrepreneurial opportunities, or develop new products or business models, they engage in a sequential search process that can be usefully conceptualized as traversing a rugged performance landscape. Our overview of the six themes and the mechanisms that contribute to effective search should thus be particularly valuable for scholars in strategy, entrepreneurship, or innovation who conduct empirical research and apply a process lens. While we have offered a number of concrete ideas for future research, we believe that the key contribution of our review is to provide a basis for scholars to better link formal and empirical research on search processes (see also Oxley, Rivkin, & and Ryall, 2010). To foster a more productive division of labor between theoretical and empirical work, empirically-minded researchers must be able to digest, draw on, and connect to the insights generated by formal work. This link is important not only because it exposes the formal results to scrutiny, but also because it allows for identification of boundary conditions and additional mechanisms that enhance or restrict the effectiveness of search processes, which can then inform additional formal work.

In addition, we believe that important insights can be gained by linking the notion of search in rugged performance landscapes to practitioner-oriented practices and frameworks, such as the lean startup or design thinking. The conceptual lens and formal apparatus of rugged landscape models hold the potential to greatly improve our understanding of these phenomena. Even more importantly, we believe that the rather abstract body of academic work identified above contains normative insights that can be translated into managerially-relevant practices.
REFERENCES


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FOOTNOTES

1 We use the term “choice” throughout to denote a dimension of the problem space. Different scholars use different terms depending on the context of the study. Examples include “attribute” (Levinthal, 1997), “decision” (Rivkin, 2000), “policy choice” (Ghemawat & Levinthal, 2008), “influence factor” (Sommer & Loch, 2004), and “routine” (Yi, Knudsen, & Becker, 2016).

2 The rugged landscape literature builds on Stuart Kauffman’s seminal work in evolutionary biology (Kauffman & Levin, 1987; Kauffman, 1993)—the NK model—which Levinthal (1997) introduced into the management literature. A substantial amount of research in biology applies the NK model to key questions, such as evolvability (e.g., Wagner & Altenberg, 1996). In addition, there is formal work that examines the generic properties of the NK model, such as the computational complexity of NK fitness functions (Wright, Thompson, & Zhang, 2000) or closed-form results (Durrett & Limic, 2003).

3 A few studies use an alternative measure of the degree of complexity: the number of choices that one needs to “get right” in order for the joint set of choices to lead to higher performance (e.g., Fang, Lee, & Schilling, 2010). The extreme case is a “needle in the haystack” problem in which performance improves if and only if all choices are simultaneously made correctly (Bruderer & Singh, 1996).

4 We tried using several keywords, such as “NK model,” “rugged landscape,” “search,” and “complexity.” The resulting lists of articles (including those derived using combinations of these keywords) were either too narrow (i.e., many or most of the articles in our original list were not identified) or too wide (i.e., the results contained a large number of irrelevant articles). We therefore used Levinthal (1997) as a starting point.

5 We did so to account for the fact that relevant studies may be regularly published in management journals that are not on the FT50 list (e.g., Industrial and Corporate Change or Strategic Organization).

6 Among the formal modeling studies citing Levinthal (1997), 62 were rugged landscape simulation studies. Of these, 46 were on our original list. Notably, our original list contained nine articles that were not listed in Web of Science. Four of these had been accepted for publication as of December 31, 2017, and were therefore not yet listed in Web of Science. The others were published in either Industrial and Corporate Change or Strategy Science, which are or were originally not included in Web of Science.

7 One simulation study included in our review (Winter, Cattani, & Dorsch, 2007) does not use a variant of the NK model to model a rugged landscape. Instead, it uses a modeling approach based on fractal geometry.

8 Broad search is sometimes characterized as “exploration” in the articles we review here. However, as “exploration” may have different meanings in other contexts, we do not use the term here. In addition, one needs to be careful when drawing inferences about what the results of landscape simulation models may mean for exploration more broadly (Uotila, 2017a).

9 There is a relatively large stream of literature (with a strong focus on product development and innovation) that empirically examines the effect of modular product structures on a variety of outcomes (sometimes comparing modular and less modular structures; see, e.g., Sosa, Eppinger, & Rowles, 2004). However, this stream of literature does not substantially build on the simulation studies we review here. Therefore, we only include empirical work from this literature stream that explicitly accounts for a search process.
### Table 1
Simulation Studies by Journal

<table>
<thead>
<tr>
<th>Journal</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Management Science</td>
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<tr>
<td>Organization Science</td>
<td>19</td>
</tr>
<tr>
<td>Strategic Management Journal</td>
<td>7</td>
</tr>
<tr>
<td>Administrative Science Quarterly</td>
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</tr>
<tr>
<td>Industrial and Corporate Change</td>
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</tr>
<tr>
<td>Strategic Organization</td>
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<td>Academy of Management Review</td>
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</tr>
<tr>
<td>Strategy Science</td>
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<tr>
<td>European Management Review</td>
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<tr>
<td>Academy of Management Journal</td>
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<tr>
<td>MIS Quarterly</td>
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<tr>
<td>Industrial Marketing Management</td>
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<tr>
<td>Journal of Business Venturing</td>
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<tr>
<td>Small Business Economics</td>
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<td>Journal of International Management</td>
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### Table 2
Problem Structure Types, Themes and Sub-themes, and Coding Scheme

<table>
<thead>
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<th>Problem structure types</th>
<th>Code</th>
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<tbody>
<tr>
<td>Unstructured interdependencies</td>
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<tr>
<td>Modular interdependencies</td>
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<tr>
<td>Nearly-decomposable systems</td>
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<td>Hierarchical interdependencies</td>
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</tr>
<tr>
<td>Number of choices to get right</td>
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</tr>
<tr>
<td>Other landscape-generating approach</td>
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</table>

<table>
<thead>
<tr>
<th>Theme</th>
<th>Sub-theme</th>
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</thead>
<tbody>
<tr>
<td>1. Learning mode</td>
<td>Experiential learning</td>
</tr>
<tr>
<td></td>
<td>Vicarious learning and imitation</td>
</tr>
<tr>
<td>2. Problem decomposition</td>
<td>Constraining the set of choices</td>
</tr>
<tr>
<td></td>
<td>Partitioning the problem</td>
</tr>
<tr>
<td>3. Cognitive representation</td>
<td>Insights into superior solutions</td>
</tr>
<tr>
<td></td>
<td>Insights into the problem structure</td>
</tr>
<tr>
<td></td>
<td>Changing representation</td>
</tr>
<tr>
<td>4. Temporal dynamics</td>
<td>Sequencing</td>
</tr>
<tr>
<td></td>
<td>Time constraints</td>
</tr>
<tr>
<td>5. Distributed search</td>
<td>Parallel search</td>
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<tr>
<td></td>
<td>Coupled search</td>
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<tr>
<td>6. Search under competition</td>
<td>Heterogeneity</td>
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<td></td>
<td>Competitive dynamics</td>
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### Table 3
List of Articles, Context, Themes, and Key Results

<table>
<thead>
<tr>
<th>Article</th>
<th>Context</th>
<th>Problem structure</th>
<th>Learning mode</th>
<th>Problem decomposition</th>
<th>Representation</th>
<th>Temporal dynamics</th>
<th>Distributed search</th>
<th>Competition</th>
<th>Key result</th>
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<tr>
<td>Levinthal (1997)</td>
<td>Adaptation and heterogeneity</td>
<td>K E - - - -</td>
<td>H</td>
<td>Complexity affects heterogeneity among organizations.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>McKelvey (1999)</td>
<td>Co-evolution and competitive advantage</td>
<td>K E - - P D</td>
<td>D</td>
<td>Interdependencies among competitors affect opportunities for competitive advantage</td>
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<td>Gavetti &amp; Levinthal (2000)</td>
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<td>Even coarse insights into solutions can give firms a head start in the search process.</td>
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<td>Marengo, Dosi, Legrenzi, &amp; Pasquali (2000)</td>
<td>Division of labor</td>
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<td>Problem decomposition has important performance implications when search efforts are distributed.</td>
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<td>Rivkin (2000)</td>
<td>Imitation</td>
<td>K V - - - -</td>
<td>H</td>
<td>Complexity is an effective isolating mechanism.</td>
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<td>Rivkin (2001)</td>
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<td>K V - - - -</td>
<td>H</td>
<td>Intermediate levels of complexity allow for internal replication and impede imitation by competitors.</td>
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<td>Sequential search should focus on choices in the order of their contributions, but account for interdependencies.</td>
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<td>K</td>
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<td>P</td>
<td>ST</td>
<td>-</td>
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<td>When competition is intense, centralized organizations have an advantage over decentralized ones.</td>
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<td>Dosi, Levinthal, &amp; Marengo (2003)</td>
<td>Coordination and cooperation</td>
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<td>E</td>
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<td>P</td>
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<td>Interdependent product components can lead to problem-solving oscillations.</td>
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<td>Mihm, Loch, &amp; Huchzermeier (2003)</td>
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<td>When units are interdependent and have search capabilities, hierarchical control is particularly beneficial.</td>
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<td>Rivkin &amp; Siggelkow (2003)</td>
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<td>C</td>
<td>-</td>
<td>Temporal decentralization can be superior to continuous centralization or decentralization.</td>
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<td>Within-unit adaptation and efforts to improve problem partitioning are complementary.</td>
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<td>It is better to decompose a problem into too few modules than too many.</td>
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<td>Ethiraj &amp; Levinthal (2004b)</td>
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<td>V</td>
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<td>In contexts characterized by unknown unknowns and high complexity, trial-and-error learning is often preferable to multiple parallel trials.</td>
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<td>Sommer &amp; Loch (2004)</td>
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<td>Letting subordinates select a problem representation is often superior to imposing representations from the top.</td>
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<td>-</td>
<td>I</td>
<td>-</td>
<td>C</td>
<td>-</td>
<td>More analogies are better than details, and analogies are most useful when problems do not have a modular structure.</td>
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## EFFECTIVE SEARCH IN RUGGED LANDSCAPES

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<td>Chao &amp; Kavadias (2008)</td>
<td>Product development</td>
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<td></td>
<td>Environmental complexity increases the relative share of radical innovation projects in optimal product development portfolios.</td>
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<td>Ethiraj, Levinthal, &amp; Roy (2008)</td>
<td>Modularity and imitation</td>
<td>K</td>
<td>V</td>
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<td></td>
<td></td>
<td></td>
<td>Modular designs are beneficial for internal innovation, but they are susceptible to external imitation.</td>
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<td>Ghemawat &amp; Levinthal (2008)</td>
<td>Strategy as commitment</td>
<td>H</td>
<td>E</td>
<td>R</td>
<td>P</td>
<td>C</td>
<td></td>
<td>Early commitment to important choices is better than unconstrained search.</td>
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<td>Ethiraj &amp; Levinthal (2009)</td>
<td>Performance goals</td>
<td>K</td>
<td>M</td>
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<td></td>
<td></td>
<td>Lock-in from multiple goals can be overcome by changing goals over time or distributing them in the organization.</td>
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<td>Ganco &amp; Agarwal (2009)</td>
<td>Market entry</td>
<td>K</td>
<td>M</td>
<td>V</td>
<td>-</td>
<td></td>
<td>D</td>
<td>Diversifying entrants outperform entrepreneurial start-ups when turbulence is high, while learning favors start-ups.</td>
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<td>Siggelkow &amp; Rivkin (2009)</td>
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<td>A</td>
<td>PO</td>
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<td>Coupled search among both strategic and operational choices can obscure the performance implications of the former.</td>
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<td>Almirall &amp; Casadesus-Masanell (2010)</td>
<td>Open innovation</td>
<td>K</td>
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<td>Divided search is superior for less complex problems, while integrated search is superior for more complex problems.</td>
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<td>Fang, Lee, &amp; Schilling (2010)</td>
<td>Organizational structure</td>
<td>J</td>
<td>V</td>
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<td>P</td>
<td>Semi-isolated subgroups help diffuse good practices while maintaining the diversity needed to allow for further improvements.</td>
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<td>Mihm, Loch, Wilkinson, &amp; Huberman (2010)</td>
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<td>Centralized decision making (hierarchy) can improve search processes when problems are complex.</td>
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<td>Aggarwal, Siggelkow, &amp; Singh (2011)</td>
<td>Alliance governance</td>
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<td>Different interdependency structures require different alliance governance modes.</td>
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<td>Millhiser, Coen, &amp; Solow (2011)</td>
<td>Team staffing</td>
<td>KM E</td>
<td>P</td>
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<td>Under many circumstances, equitably distributing workers across teams is not the most effective staffing policy.</td>
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<td>Butler &amp; Grahovac (2012)</td>
<td>Markets, hierarchies, and teams</td>
<td>J E</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>The effectiveness of teams, markets, and hierarchies depends on complexity, information conditions, and learning abilities.</td>
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<td>Marengo &amp; Pasquali (2012)</td>
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<td>K E</td>
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<td>-</td>
<td>C</td>
<td>When the right direction is unknown, delegation and intervention must balance control and learning.</td>
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<td>Andries &amp; Debackere (2013)</td>
<td>Business-model innovation</td>
<td>K E R</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Complexity, ambiguity, and experience affect how firms should learn about business-model improvements.</td>
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<td>Baumann &amp; Siggelkow (2013)</td>
<td>Product-development process</td>
<td>KH E R P ST</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>It is better to gradually increase complexity than to design an entire complex system from the start.</td>
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<tr>
<td>Posen, Lee, &amp; Yi (2013)</td>
<td>Imitation</td>
<td>K V</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Imperfect imitation is superior to perfect or random imitation because it prevents premature lock-in and reduces diversity.</td>
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<td>Adner, Csaszar, &amp; Zemskey (2014)</td>
<td>Strategic positioning</td>
<td>K E</td>
<td>-</td>
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<td>In the presence of multiple performance dimensions, complexity often implies lower organizational heterogeneity.</td>
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<td>Jain &amp; Kogut (2014)</td>
<td>Organizational adaptation</td>
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<td>Organizational memory improves evolvability when drift is possible and change is costly.</td>
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<td>Knudsen &amp; Srikanth (2014)</td>
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<td>O</td>
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<td>Coordinated exploration by multiple specialists is subject to pathologies of search that are not present in unitary search.</td>
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<td>Claussen, Kretschmer, &amp; Stieglitz (2015)</td>
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<td>M</td>
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<td>Mihm, Sting, &amp; Wang (2015)</td>
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<td>Miller &amp; Lin (2015)</td>
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<td>Csaszar &amp; Levinthal (2016)</td>
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<td>Yi, Knudsen, &amp; Becker (2016)</td>
<td>Organizational routines</td>
<td>K</td>
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The rate of scale adjustments, in conjunction with adjustment error, can serve as a dynamic isolating mechanism.
Trust in supply chains depends on patterns of interdependency among firms.
The interdependency structure between national units affects the optimal structure of multi-national companies.
The benefits of integration (relative to non-integration) first increase and then decrease with rising turbulence.
Plasticity (the capacity to adapt behavior) poses a trade-off between learning and the effectiveness of selection processes.
An optimal patenting strategy is contingent upon R&D strategy, the technology landscape, and competitor behavior.
The accuracy of analogical reasoning depends on environmental dynamism, unpredictability, and complexity.
In offshoring, learning is affected by communication costs, geographical distance, and noise in performance signals.
The value of searching for a better representation is higher when complexity is higher and when time is not limited.
Routine-level inertia can be beneficial for organization-level adaptation.
## EFFECTIVE SEARCH IN RUGGED LANDSCAPES

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<td>Gavetti, Helfat, &amp; Marengo (2017)</td>
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<td>D</td>
<td>Shaping others' payoffs entails an advantage under conditions of high complexity or when only a few dimensions can be affected.</td>
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<td>Querbes &amp; Frenken (2017)</td>
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<td>Whether late movers have an advantage depends on whether incumbents are constrained in changing their prior choices.</td>
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<td>Both turbulence and complexity generate a punctuated equilibrium pattern.</td>
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<td>Podolny (2018)</td>
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See Table 2 for the list of codes used in categorizing the articles in this table.
Note: This figure illustrates, in a stylized manner, how search is affected by the complexity of the underlying problem. If complexity is low in the sense that the decisions related to the problem are independent, the resulting performance landscape is smooth and contains only a single peak (Panel A). In this case, local search always leads to the peak, regardless of the starting point. If complexity is high and decisions have many interdependencies, the landscape becomes rugged and contains many local peaks (Panel B). In this case, starting with a random solution (the “starting point”) and improving the solution along one dimension (e.g., Dimension 1) leads to one of the many local peaks (marked “local peak”). From there, reaching a higher local peak or even the global peak requires adjustments along both dimensions.
ONLINE APPENDIX: GLOSSARY

The following offers an overview and brief descriptions of key terms used within the rugged landscape literature (an → in front of a term indicates that this term is also included in the glossary).

**Agent.** An agent is an entity that searches for a → solution to a → problem. Multiple agents may search simultaneously and their search processes may be interdependent in multiple ways (→ coevolution).

**Broad search.** The broader a search process, the greater the number of potential solutions (in other words, the larger the part of the landscape that can be reached through the search process). Local search is narrow because it leads to → hill climbing and a → local peak. A broadening of the search process increases the expected → performance of the → peak (the solution ultimately reached by the search process).

**Coevolution.** When multiple agents are interdependent, their search processes coevolve. The most relevant forms of coevolution in the rugged landscape literature are → coupled search and → parallel search.

**Cognitive representation.** A cognitive representation is an agent’s representation of the features of a → problem and/or its → solution space. Cognitive representations facilitate the agent’s search process.

**Complexity.** Multiple definitions of complexity exist (see Gell-Mann, 1997, for a brief, non-technical overview). Within the rugged landscape literature, complexity is understood in terms of a → problem that has both a large number of choices and numerous interdependencies among choices (Simon, 1962). The number of choices is represented by the parameter N and the degree of complexity by the parameter K. Specific complex problem structures (e.g., modular problems) can be represented by
specifying the interaction matrix. Complexity affects the landscape’s topology, such that a higher degree of complexity leads to more peaks.

**Coupled search.** When each of two or more agents only searches across a subset of all choices but their choices are interdependent, then their search processes are coupled. Due to these interdependencies, coupled search processes lead to sticking points instead of local peaks. Coupled search is a form of coevolution.

**Distant search.** The distance between two solutions is the number of choices in which they differ (this is called “Hamming distance”). A local search process cannot immediately reach a solution with a Hamming distance of two or more from the current solution.

**Evaluation.** The process by which the performance of one or more candidate solutions is examined and compared with the current solution is called evaluation. Evaluation may be subject to imperfections. A typical distinction is between online evaluation (using feedback generated from experiential search by “trying out” the candidate solution) and offline evaluation (using other means for evaluation, such as a cognitive representation).

**Exploration.** This generic term denotes the search for and identification of superior solutions that depart from and are different from currently known solutions (see March, 1991, for an overview and application to the management literature). In the rugged landscape model literature, exploration is associated with broad search.

**Hill climbing.** See local search.

**Imitation.** Imitation is the adoption of the values for a set of choices from another agent from the same population (and replacing one’s own previous values for these choices).
**Interaction matrix.** An interaction matrix captures the interdependencies among choices. See Rivkin and Siggelkow (2007) for an overview of interaction matrices that represent typical problem structures.

**Interdependence.** Two choices are interdependent when the value of one choice affects the performance of the value for the other choice. Interdependencies can be sequential (i.e., one choice affects another but not vice versa) or reciprocal (i.e., two choices affect each other). The set of interdependencies is specified via the interaction matrix. In coupled and parallel search processes, interdependencies among choices lead to interdependencies among agents.

**Local search.** A local search process can identify superior solutions only in its “neighborhood.” In other words, any candidate solution differs from the current solution in only one dimension. When local search is “hill climbing” (only solutions that are superior to the current solution are adopted), it moves towards a local peak.

**Local peak.** See peak.

**Modularity.** A specific problem structure in which there are two or more subsets of choices (“modules”) that exhibit strong interdependencies among choices of the same subset, while there are only few or no interdependencies among choices that are part of different subsets. A modular problem with few interdependencies among modules is “near-decomposable” (Simon, 1962).

**Near-decomposability.** See modularity.

**Parallel search.** When multiple agents search across the same set of choices, then their search processes are parallel. If the agents are also interdependent, then their parallel search is a form of coevolution.

**Partitioning.** Partitioning involves dividing the problem into subsets in order to divide the search process across multiple agents (see coupled search).
**Peak.** A solution for which performance cannot be improved through local search. The solution with the highest performance constitutes the global peak. All other peaks are local peaks. Local peaks vary in their performance. A higher degree of complexity leads to more peaks.

**Performance measures.** This entails the mapping of the combination of choices (accounting for interdependencies among choices and, potentially, other parameters) onto a measure of “success” (e.g., “performance,” “outcome,” “pay-off”). Performance measures can be multi-dimensional (i.e., the same choices may map onto multiple measures). There may be performance measures for a subset of choices (as is often the case in coupled search, in which case a search process may lead to a sticking point instead of a local peak). The performance mapping determines the landscape’s topology, including the “height” of the various peaks.

**Population.** A population is a set of agents who search across the same choices (parallel search). A population may represent, for example, multiple organizations that are in competition or multiple projects carried out within the same organization. Multiple populations may have coupled search processes, which leads to co-evolution.

**Problem.** A problem is a set of choices for which agents search for a solution.

**Search.** Search is a process by which superior solutions are discovered through a sequential process. A search process starts with an initial solution. At each step, one or more candidate solutions are evaluated by comparing their performance with the current solution.

**Solution.** A solution is a combination of values for each choice that maps onto a performance measure. The solution space is given by mapping all combinations onto performance outcomes (topology).
**Sticking point.** When the performance measures of agents in a coupled search process only take into account a subset of choices, the search process may lead to a sticking point instead of a local peak.

**Topology.** The solution space, including peaks. See performance measures.