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RUUTU (Sampsa), WINDRUM (Paul), HYYTINEN (Kirsi), TOIVONEN (Marja), TUOVILA (Hannamaija), « Hétérogénéité de la demande, décomposabilité et coordination de l'innovation de service dans les organisations multi-unités »

RÉSUMÉ – Cet article présente un modèle computationnel de recherche organisationnelle qui compare différentes stratégies d'organisation de l'innovation de service dans une organisation multi-unités : centralisation, décentralisation et partition de l'innovation entre différentes unités opérationnelles. La performance est comparée pour différents degrés de décomposabilité des problèmes et différents niveaux d'hétérogénéité de la demande. Les résultats sont illustrés par une étude de cas dans le secteur de la santé.

MOTS-CLÉS – Innovation de service, santé, modèle NK, simulation, recherche organisationnelle

RUUTU (Sampsa), WINDRUM (Paul), HYYTINEN (Kirsi), TOIVONEN (Marja), TUOVILA (Hannamaija), « Demand heterogeneity, decomposability, and the coordination of service innovation in multi-unit organizations »

ABSTRACT – This article presents a computational model of organizational search that compares different strategies of organizing service innovation in a multi-unit organization: centralisation, decentralisation, and partition search conducted by the different business units on a specific part of the innovation. The performance is compared for varying degrees of problem decomposability and varying levels of demand heterogeneity between units. It illustrates the findings using a case study from the health care sector.

KEYWORDS – Service innovation, health care, NK model, simulation, organizational search

DEMAND HETEROGENEITY, DECOMPOSABILITY, AND THE COORDINATION OF SERVICE INNOVATION IN MULTI-UNIT ORGANIZATIONS

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INTRODUCTION

A key question for multi-unit organizations is how to coordinate innovative activity across their business units. An extensive literature exists on structural ambidexterity (cf. March, 1991; Benner and Tushman, 2003; Gibson and Birkinshaw, 2004). The general recommendation is that business units operating in different industry sectors should be structurally independent in order for innovative activity appropriate for its particular industry and its stage of the innovation life cycle. For example, a business unit should engage in incremental development of an existing technology base (“exploitation”) if it operates in a relatively

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mature product market. Alternatively, a business unit should engage in radical (“exploratory”) R&D if it is prospecting within a new technology market.

While existing research has compared bottom-up entrepreneurial and top-down managerial ways of organizing service innovation (Sørensen *et al.*, 2013), there exists relatively little discussion about how a multi-unit organization, operating within one industrial sector, should organize its innovation. One way is to allow each unit to develop solutions autonomously. A key advantage is that local solutions can be tailored to the needs of each unit. Decentralised decision-making may be needed if specialised knowledge resides at lower levels of the organizational hierarchy, or if the formal authority holder’s cognitive capacity is overloaded because of the need to make many decisions (Dobrajska *et al.*, 2015). Decentralised innovation, it is suggested, may be more sensitive to changes in the local market/business environment (Czasar, 2012; Sah and Stiglitz, 1986).

Directed (top-down) innovation is an alternative means of organizing activities within a multi-unit organization. Here one unit conducts R&D and subsequently rolls out the new product/service to all other units. An advantage of this hierarchy is that innovation decisions can be framed against medium to long-term changes in the global business-social-political environment (Jacobides, 2007; Marengo and Dosi, 2005). Decentralised decision-making may be linked to narrow decision frames, which may ignore systemic changes in the wider operating environment (Luoma 2013).

A third strategy is partition. Here the innovation problem is broken down into a number of elements (also see Siggelkow and Levinthal, 2003). For example, the design of a service product may be broken down into a number of different “modules” that, together, make up a final service. Innovation within each service module may be tackled by one, or several, business units within the organization. Each modular innovation is to be combined. The partition strategy has not previously been considered by authors within the literature on innovation within multi-unit organizations where each business unit serves its own segment of customers.

The paper analyses these three strategies through a computational model of multi-unit organizational search. We find that the efficacy of each search strategy depends on (a) the degree of heterogeneity of

customer preferences faced by business units, and (b) the decomposability of the innovation problem. We illustrate the potential advantages of partition strategy using a case study of a health care reform within a regional provider of primary health care services in Finland.

I. THEORETICAL BACKGROUND

The organization of productive activity by the firm has been examined using transaction cost economics and the knowledge based theory of the firm (Colfer and Baldwin, 2010). In transaction cost economics (Williamson, 1985), the focus is on aligning incentives in order to achieve cooperation between actors. By contrast, the knowledge based theory of the firm focuses on the information flows and communication required for organizing tasks, and examines how different organizational structures correspond to different search problems (Colfer and Baldwin, 2010). This paper is within the knowledge-based approach. We assume that all business units operating within a multi-unit organization are willing and motivated to cooperate but are limited by their information processing capabilities. Given this, the problem is how to organise innovation within a multi-unit organization.

We view the multi-unit organization as a complex system that consists of multiple “elements” (in this case, a set of service modules that together make up an overall service) and a set of interactions between these elements. The complex system approach has been applied in a number of disciplines, such as the design of complex engineering systems (e.g. Baldwin and Clark, 2006; Colfer and Baldwin, 2010), service innovations (Gallouj and Weinstein, 1997; Chae, 2012), innovations in general (e.g. Murmann and Frenken, 2006; Frenken, 2006), and organizational design (e.g. Ethiraj and Levinthal, 2004). In the characteristics-based approach to services the underlying technological and organizational design of a service (its “technical characteristics”), together with the competences of service providers and their clients, determine the quality and overall performance of a service (its “service characteristics”) (Gallouj and Weinstein, 1997; Windrum and García-Goñi, 2008).

Improvements in service characteristics can arise through organizational search for new technologies, and/or the adoption of new routines for delivering services (Nelson and Winter, 1982; Windrum and García-Goñi, 2008; Chang and Harrington, 2006). However, interdependencies between the modules (elements) are non-linear and make the search problem complex. This can be modelled as a process of hill climbing with a fitness landscape, where complexity is characterised as a landscape that is “rugged”, containing multiple peaks. There is a possibility that an organization searching a rugged landscape can become trapped on a local (sub-optimal) peak, and fails to reach the optimal service design (represented by the highest peak within the fitness landscape).

In addition to non-linear interactions between system elements, the distribution of interdependencies across elements (here, the modules that comprise a service) also affects search. If the innovation problem can be decomposed into a number of different sub-problems, then individual business units can be assigned to these sub-problems. However, hierarchical coordination is needed when services are only partly decomposable (Nickerson and Zenger, 2004).

Search performance can be evaluated both in the short term and in the long term. In the short term, rapid learning is important under conditions of severe competition. This may be due to strong selection pressures in the industry (Marengo and Dosi, 2005); it may be due to a reinforcing feedback loop, existing between capability and performance, that needs to be activated before competitors (Chang and Harrington, 2003; Rahmandad, 2012); or it may be due to large market fluctuations (Chang and Harrington, 2000). Under these conditions, decentralised and parallel search may be effective for reaching a local (sub-optimal) peak (Marengo and Dosi, 2005). In the long term, however, a key question is whether different means of organising innovation search are more or less effective in escaping local optima and identifying the global peak.

In a multi-unit organization, the central unit may perform one of a number of different roles. The existence of superior resources and capabilities for innovation, vis-à-vis other business units within the organization, may prompt centralised innovation arrangements (“top-down” innovation in Sørensen *et al.*, 2013), for example through a centralised R&D department.

Alternatively, the central unit may take on an enabling function, facilitating the transfer of information and knowledge between units in order to support a decentralised, practice based innovation structure (“bottom-up” innovation arrangements in Sørensen *et al.*, 2013). A key aspect of this is ensuring that the practices of different units within the organization are compatible, as this is important for knowledge transfer between different units (Chang and Harrington, 2000).

A third alternative is that the central unit guides the search efforts of other units by defining and constraining their search to specific sub-problems. Nickerson and Zenger (2004) refer to this as “authority-based hierarchy”. The same authors note that knowledge sharing is required where actors have a simplified (lower dimensional) mental model of the search landscape, which guides the direction of search (also see Gavetti and Levinthal, 2000). Nickerson and Zenger (2004) argued that this kind of a cognitive heuristic search (instead of a local search based on trial and error learning) is needed for complex and non-decomposable problems.

Chang and Harrington (2006) distinguish between, on the one hand, business units that focus on different parts of the value-adding process (e.g. functionally differentiated operations such as production, sales, marketing) (see, e.g. Rivkin and Siggelkow, 2003; Siggelkow and Levinthal, 2003; Siggelkow and Rivkin, 2006) for the same product market, and, on the other hand, where different organizational units provide services to different customer segments or markets, independently of each other. The latter is more relevant for the purposes of this paper.

The issue of information and knowledge transfer between different business units within a multi-unit organization has previously been examined, using computational modelling, by Chang and Harrington (2000, 2003, 2004) in the context of retail chains, and by Kollman *et al.* (2000) in the context of public policy. The work of Kollman *et al.* (2000) is of particular interest. They used an NK model to compare four search strategies, each representing a different form of centralised or decentralised search. Two of these – what they call “centralism” and “local autonomy” – have been discussed above. “Centralism” involves the central unit searching and then imposing its solution(s) on all other business units. “Local autonomy” is where each business unit acts independently and autonomously. Each unit performs its own local

search and implements the solutions it identifies. There is no sharing of knowledge or learning between business units.

The third search strategy examined by Kollman *et al.* (2000) is “best adoption”. Here, all business units initially undertake independent search. The central organization compares the outcomes of the search undertaken by the business units and, imposes, on all units, the “best solution” which has been found. For problems of intermediate complexity, multiple decentralised units acting as “policy laboratories” can be more effective in exploring the search space than a single unit equipped with more sophisticated search capabilities.

The fourth search strategy is “incremental adoption”. Once again, each business unit initially engages in an independent search. Thereafter, each business unit moves towards the best-found solution incrementally and is free to take into account (to a greater or lesser degree) the outcomes of other business units. This is a form of parallel processing. Kollman *et al.* (2000) argue that this arrangement is effective when a problem can be decomposed into sub-problems and these can be solved in parallel. In such situations, incremental adoption may be effective in combining partial solutions.

A complex technological search problem can be broken down into a set of sub-problems, or “modules” (cf. Langlois and Robertson, 1992; Baldwin and Clark, 2006). Trial-and-error learning can be accelerated through parallel work, with different firms focusing on different modules. As well as allowing technology space to be more completely covered than would be the case by a single firm, the establishment of interfaces between modules means that technical changes in one module do not require changes in other modules.

Modularising a complex system is, however, a complex endeavour in itself. The findings of Ethiraj and Levinthal (2004) suggest that erring on the side of too much modularity can be more detrimental than too much integration. Also, we have noted that problem complexity is not only due to non-linear interactions between system elements, but also due to the distribution of interdependencies across different business units. If the search problem is completely decomposable, individual sub-problems can be solved locally (using local markets). Hierarchical coordination is needed when problems are partly decomposable. In a partly decomposable system, distinct technical practices are in place

in different parts of the system, and changes in one part need to be accommodated by changes in the technical practices of other parts of the system. This may decrease overall performance in the short term.

II. MODEL DESCRIPTION

The model presented in this paper is novel in two ways. First, one can vary the degree of problem decomposability whilst keeping the number of interactions between service modules (elements) constant. By so doing, one can focus on the effects of problem decomposability. Prior research, for example by Nickerson and Zenger (2004), and Kollman *et al.* (2000), has examined the effect of changes in the number of interactions only.

A second novelty of the model is that one can systematically examine the effect of heterogeneous demand for the services produced by different business units belonging to a multi-unit organisation, and the interaction effect of heterogeneous demand with problem decomposability. For example, Kollman *et al.* (2000) recognised that the relative performance of different search strategies depends on demand heterogeneity between units but did not explore it systematically. Chang and Harrington (2000, 2003, 2004) did consider the effect of customer heterogeneity in their model of a multi-unit organization, but they did not examine how heterogeneity interacts with the decomposability of the search problem².

We model organizational search using the NK modelling approach. The approach has its origins in evolutionary biology (Kaufman, 1993) but has been used to study issues in a wide range of fields, such as organizational strategy (e.g. Ganco and Hoetker, 2009) and innovation (e.g. Frenken, 2006).

In the NK approach, the system under study is viewed as an ensemble of N design elements (represented as a binary bit string, i.e. a string that contains a fixed number of bits that can either take the value of 0 or 1)

2 The modelling approach of Chang and Harrington is very different to that developed here. They construct a model based on economic primitives, such as purchased quantities at a given price. Ours is based on the NK model in which random fitness landscapes are created.

and K interrelationships between these elements. The contribution of each element to the performance of the whole system (or “fitness” on a search landscape) depends not only on the value of the element itself but also on the values of the elements to which it is linked. A “design” is a particular configuration of design elements, and each design is assigned a fitness value. In terms of modelling innovation, the overall fitness of a design is measured in terms of service characteristics space. Local peaks within this service characteristics (fitness) landscape is given by a set of consumer preferences for these service characteristics.

At the start of a simulation run, each business unit belonging to the multi-unit organization is randomly allocated an initial position on a landscape. Depending on the degree of heterogeneity (see below), each business unit may be searching its own landscape, or all units may be searching identical landscapes.

Business units engage in directed (local) search, i.e. they seek to improve their position in service characteristics space by altering the technical characteristics of their designs. The ultimate goal is to identify the “optimal” design configuration (containing that unique combination of “0” and “1” values across all service modules) that produces the highest fitness – i.e. it has an optimal performance given heterogeneous demand and the degree of decomposability of the service design.

As is common within an NK framework, we assume that the search capabilities of an agent is constrained and, hence, it engages in “local search” that is incremental. As such, search involves incremental movement around the fitness landscape, as one or more business units seek to incrementally improve their service offerings. In each simulation period, one element of a string of binary bits can be altered (by switching a “0” to a “1” or vice versa). If this is fitness improving, then we assume the organization can undertake and implement an improvement in the service characteristics it offers to users. In the event there are more than one options that improve fitness, the organization will pick one of these options at random (cf. Levinthal, 1997).

The focus of this model is the impact of heterogeneous demand and decomposability on innovation. To simplify, we assume that the supply side competences of each business unit are in place, and do not differ across units (except for the central unit in the centralisation search strategy). In practice, business units within the same organization may

differ in their competence to undertake innovation, and, hence, this may affect their search processes.

In the following sections, we discuss how heterogeneous demand and decomposability of the search problem are operationalised in our model.

Model equations are provided in the Appendix. The model has been implemented using Python 3.5.

II.1. HETEROGENEOUS DEMAND

Within our model, each business unit within a multi-unit organization is assigned to a particular set of customers. The preferences of each consumer group differs. For example, in the context of a health care organization providing services across a geographical region (see the case study below), service demand can vary significantly depending on differences in the environment (urban vs. rural) and the demographics of the user population (e.g. age). Hence, patients in one local demographic group may prefer a certain kind of health care service, whereas for another group an alternative version of the service would be better.

We assume that the landscapes faced by business units belonging to the same organization are partly correlated³. Whilst there are differences in the demand (consumer preferences) faced by different business units, it seems reasonable to assume that the preferences are correlated to some degree.

This is modelled by creating different fitness components (joint fitness landscape component of all units and a unique fitness landscape component of each unit) and then calculating the overall fitness for each unit using a weighted average. By varying the weights of the joint fitness landscape and the unique landscape component of each unit, we are able to vary the correlation between 0 and 1. A correlation of 1 indicates that identical fitness landscapes are being searched by two or more business units. In this case, a particular configuration of technical characteristics would yield the same benefit for the customers for all units. By contrast, a correlation of 0 indicates that the fitness landscapes

3 An alternative modelling formulation would be for consumers to assign different weights to the design elements, to reflect differences between the local patient populations (as in, for example, Frenken and Nuvolari, 2004). In this case, the assumption is that different customers value different aspects differently (e.g. for some patients e-health would be important, whereas for others it would be insignificant).

II.2. DECOMPOSABILITY OF THE SEARCH PROBLEM

In a fully decomposable system, interactions exist between design elements within a module, but there are no interactions between elements belonging to different modules. As discussed above, the key advantage of a fully decomposed system is that changes made to one module do not require changes to other modules. By contrast, in a partly decomposable system, a change in one module requires accommodating changes to be made in one or more other modules to ensure that modules work together.

We alter the decomposition of the search problem in our model in the following way. Starting from a fully decomposable system, we vary the degrees of decomposability by randomly changing the links in the system. The larger the number of changes specified in the model, the lower the degree of problem decomposability. After a large number of changes, the system is completely non-decomposable, and, on average, there is an equal probability that a link exists between any two elements. By specifying the number of changes, we are able to create systems of varying degrees of problem decomposability.

Figure 2 provides a graphical illustration of a system where $N=12$. The top row corresponds to a situation with $K=5$, and the bottom row corresponds to a situation with $K=3$. The number of elements within a module is equal to $K+1$, and elements that belong to the same module are shown in the figure with the same colour. The number of modules is equal to $N / (K+1)$.

When the number of change iterations is 0 (left column), each element within a module is linked to every other element within the same module. This is the fully decomposable structure. The centre column shows the effect of one iteration of random changes, and corresponds to a partly decomposable system. The right-hand side of the figure illustrates a system after 15 iterations of random changes, and corresponds to a non-decomposable system.

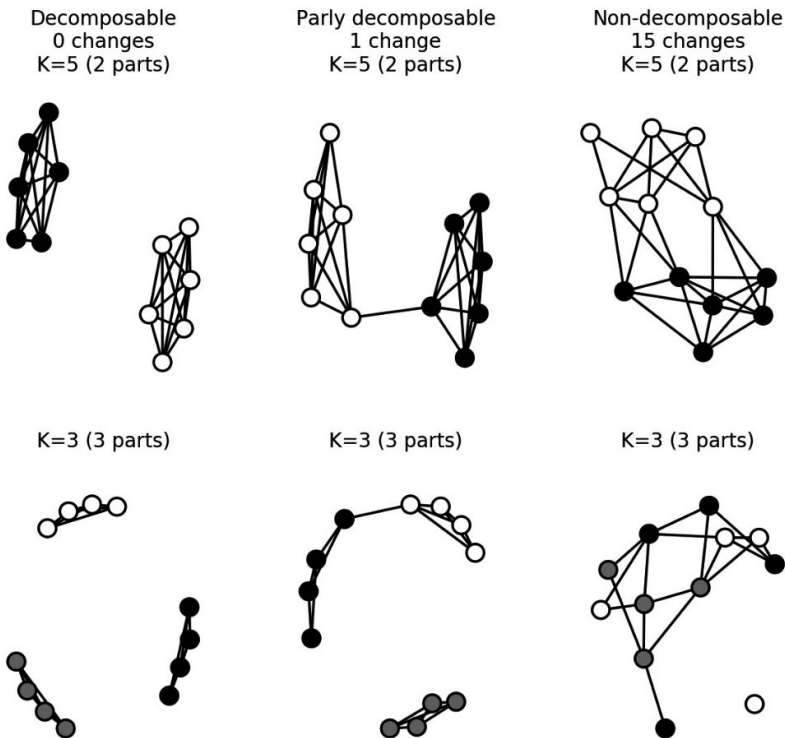


FIG. 2 – Illustrative graphical example of structures with 0, 1, and 15 iterations of random changes.

III. SIMULATION RESULTS

In this section, we first present a number of different baseline simulations in order to test the validity of our model. After this, we compare the efficacies of alternative search strategies (decentralisation, centralisation, and partition search). In our simulation experiments, the number of design elements, $N=12$. To analyse the effect of search problem complexity, we vary the value of the number of links between elements (parameter K).

III.1. BASELINE SIMULATIONS

We conducted a number of baseline simulation experiments on the model. First, we examined how altering the number of interactions (K) affects the results. This was done by creating a system in which the elements within a module are fully connected, and then comparing systems which contain two modules ($N=12$, $K=5$) and three modules ($N=12$, $K=3$).

We found that increasing the number of K interactions has two effects. First, mean average performance tends to be lower. This is because business units are more likely to become trapped on local optima. Second, the number of different end points (on the landscape) at the end of the simulation runs tend to increase. This is due to business units becoming trapped on a higher number of local peaks.

We also observed that differences in the mean fitness of the organizational units between alternative simulated landscapes decrease with an increase in the number of interactions. This can be seen in Figure 3 by comparing the range of mean fitness values of the simulations with $K=3$ and $K=5$. Each “x” and “o” in Figure 3 represents the simulation result at the end of a simulation run on a single landscape with 2^{12} organizational units.

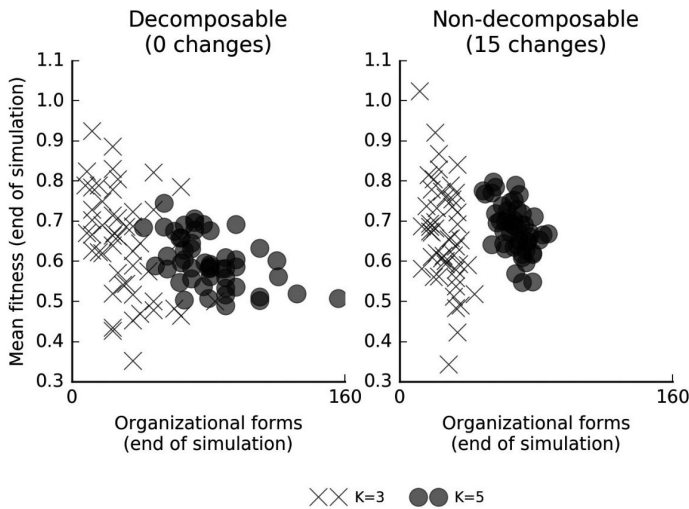


FIG. 3 – Effect of search problem complexity and decomposability on the number of distinct organizational forms and on the mean fitness.

Baseline simulations also revealed that, with the number of interconnections constant, the mean fitness at the end of the simulation runs tends to be lower when problem decomposability is high. A completely decomposable system has the lowest mean fitness. Following this, the effect of increasing the search budget is greater for a non-decomposable system, as business units are able to conduct more search before becoming trapped on local optima. In a decomposable system, business units are trapped on a larger number of local optima.

We have tested whether these results are robust when the change algorithm is varied. In the base case, the changes are symmetric, i.e. a change from $(i1, j1)$ to $(i2, j2)$ is always complemented with a change from $(j1, i1)$ to $(j2, i2)$, resulting in an undirected graph. The qualitative pattern is the same with an asymmetric change algorithm.

In the following sections, we present the findings of experiments conducted for three scenarios: (a) a relatively “easy” search problem ($K=2$; 4 modules), (b) an “intermediate” search problem ($K=5$; 2 modules), and (c) a “difficult” non-decomposable search problem ($K=11$; 1 module).

III.2. CENTRALISED AND DECENTRALISED SEARCH STRATEGIES

As discussed, a centralised search strategy involves just one unit performing innovative search. All other business units within a multi-unit organization adopt its solutions. Here we assume that it is the central unit that designs and tests a service innovation. This is then implemented by all other units within an organization. In the model, we assume that the central unit is able to conduct an extensive search of the fitness landscape (i.e. a large search distance can be covered). As such, the central unit is able to avoid being trapped on local optima. Our simulation results support the findings of Kollman *et al.* (2000) that for complex (high K) problems the benefit from a more sophisticated search is greater.

In the decentralised search strategy, each unit performs its own search. Once the units have identified their own solutions, the central unit provides information on the solution of the best performing unit to all other units. Importantly, we assume that each unit can voluntarily decide whether or not to adopt a service innovation developed by another unit. This means that units are not forced to adopt solutions that would

be inferior for them (given their particular fitness landscape). We also assume that, with decentralised search, each business unit is restricted to searching a relatively small (local) part of the fitness landscape (i.e. only a small search distance can be covered). This reflects the argument that the key benefits of decentralised search are the ability to tailor solutions to local contexts, and inter-unit learning (i.e. each unit can benefit from the solutions developed by other units within the same organization).

Figure 4 shows the comparative results for centralised and decentralised search. It shows the mean fitness values at the end of 500 simulation runs, with each run having a different landscape. The lines with dots show the results of a decentralised search for two different values of change iterations (0 and 15). The lines without dots show the results of the centralised search for two values of search distance (2 and 3).

III.2.1. Search in landscapes with varying heterogeneity

The simulation results indicate that centralised search is more effective when there is a high correlation between all units' fitness landscapes, i.e. the benefits of the more extensive search performed by of a central unit is higher the more homogeneous are the customer demands for services delivered by all units. When there are significant differences between customers' demand, it is difficult to roll out one, "general" solution to all units.

Similarly, average fitness for decentralised search tends to be higher when there is a high correlation between units' fitness landscapes. This indicates that the benefits of inter-unit learning (associated with decentralised search in this model), are greater the more homogeneous (less heterogeneous) is consumer demand. Even when there is low correlation between units' landscapes, the adoption of an innovation developed by another unit can be helpful in escaping lock-in to a local optimum. Adopting a service innovation from another unit enables a unit to commence search from a new location on its landscape.

Figure 4 also shows the marginal differences in search efficacy between these two search strategies. An increase in landscape correlation is associated with a linear increase in the performance of centralised search. When units' landscapes are completely uncorrelated, the mean fitness for a unit adopting a solution (found by the central unit) is zero. This

corresponds to the expected value of a randomly selected location on an adopting unit's fitness landscape. Examining the results for decentralised search, the lowest mean fitness also occurs when landscape correlation is zero (i.e. there is no correlation between the landscapes being searched by different units). This corresponds to a situation of totally independent local search without inter-unit learning.

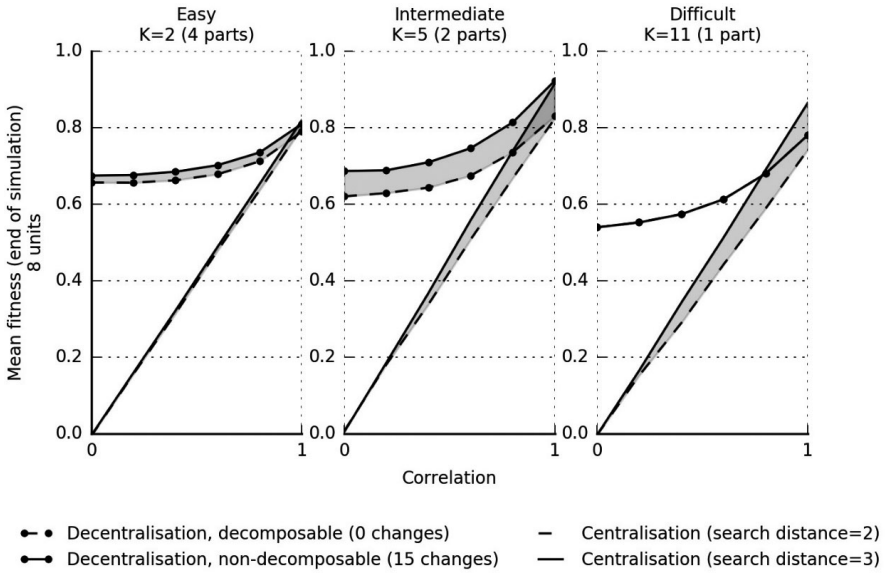


FIG. 4 – Comparative simulation results for centralised and decentralised search (for an organization with 8 units).

III.2.2. Differences in the number of units engaged in search

The findings indicate that the benefits of decentralised search depend on the overall number of business units engaged in innovative search. This is particularly so for highly complex search problems. We can understand this in the following way. When complexity is high, one unit searching a landscape is unlikely to find solutions that yield a high performance (i.e. a global optimum on its fitness landscape). The greater the number of units that search an identical landscape, the higher the probability that one of them will develop a service innovation that is optimal.

There are also benefits associated with inter-unit learning when units have landscapes with a high degree of correlation (i.e. they do not need to be identical). This is because there is a larger number of innovations for each unit to choose from. This raises the probability that there is a good solution within the set of found service innovations. This is the case even when innovation happens not to improve the fitness of the unit which developed it.

III.2.3. Differences in problem decomposability

The degree of problem decomposability affects the performance of decentralised search. This is notable, in Figure 4, when the search problem is of “intermediate” ($K=5$) complexity. For the same level of complexity, the fitness is higher when the search problem is non-decomposable. By contrast, the findings indicate that for the same level of complexity, the fitness performance of centralised search does not depend very much on problem decomposability. Because of this, when the search problem is non-decomposable, decentralised search can outperform centralised search.

III.3. PARTITION SEARCH STRATEGY

In the partition search strategy, different organizational units perform searches on specific sub-problems. Inter-unit learning occurs when units can combine their partial solutions with those found by other units of the same organization. In the model, the bit string is either searched entirely for $K=11$ (1 module), or is split into multiple parts for $K=2$ (4 modules) and $K=5$ (2 modules). Each unit is assigned a specific part to be searched. The parts are divided evenly amongst the business units. For example, when $K=5$, the search problem is split into 2 parts or modules. The first business unit searches the first six bits in the bit string, the second business unit searches bits 7–12, the third business unit again bits 1–6, and so on. At the end of each simulation run, the units can select the best combination of the obtained partitions.

III.3.1. Search in landscapes with varying heterogeneity

Figure 5 shows the findings of simulations for the partition strategy and for the decentralised strategy (discussed above). The average fitness

of the partition strategy is higher the more correlated are the search landscapes of individual business units. When the search landscapes are very different (i.e. the correlation is very low), the performance of the partition strategy can be even poorer than with decentralised local search. This is because, with the partition strategy, each unit is only able to change a limited set of their modularised services/practices, and they do not benefit from the development of partial solutions by the other units. This is a key difference to simple, decentralised search.

The simulation results also show that, for landscapes with lower correlation (i.e. more heterogeneous landscapes), average fitness using the partition strategy decreases at a lower rate than for the decentralised strategy. We note that this depends on the specific modelling assumptions which have been used in this model. We have assumed that business units have more potential solutions to choose from when using the partition strategy, and we have assumed that with decentralised search all units are only able to adopt the services/practices of the best performing unit⁴.

III.3.2. Differences in the number of units engaged in search

Comparing the mean fitness for the partition strategy in the lower and upper halves of Figure 5, we see that the benefits of partition are greater when higher numbers of business units are involved in innovative search. The higher the number of units, the larger the set of partial solutions being created. This is particularly important when the search problem is split into many parts ($K=2$; 4 modules).

The performance of the partition strategy is comparable to, or better than, decentralised search when the number of business units engaged in innovative search is high. This is because the number of possible combinations increases rapidly with an increase in the number of units engaged in search. For example, suppose the system is divided into 4 modules. If a multi-unit organization contains 4 units, then there is just one unit allocated to search per module, and there is only one combination of the partial solutions. By contrast, for a multi-unit organization

⁴ In an earlier version of the model, we tested a variant of decentralised search in which each unit could voluntarily choose any of the solutions developed by the other units. Using this formulation, fitness decreases with lower levels of landscape correlation were similar to the findings for the partition strategy.

that comprises 12 units, there can be 3 units searching within each of the 4 modules, and there are $3^4=81$ possible combinatorial solutions.

III.3.3. Differences in problem decomposability

As expected, a partition strategy is more effective (average fitness is higher) when the search problem is decomposable. The partial solutions found by different units can be effectively combined with those partial solutions found by other units. The relative effectiveness of the decentralisation and partition strategies thus depends on problem decomposability through a combination of two factors: decentralisation search by itself is less effective for decomposable problems, and partition search by itself is more effective for decomposable problems.

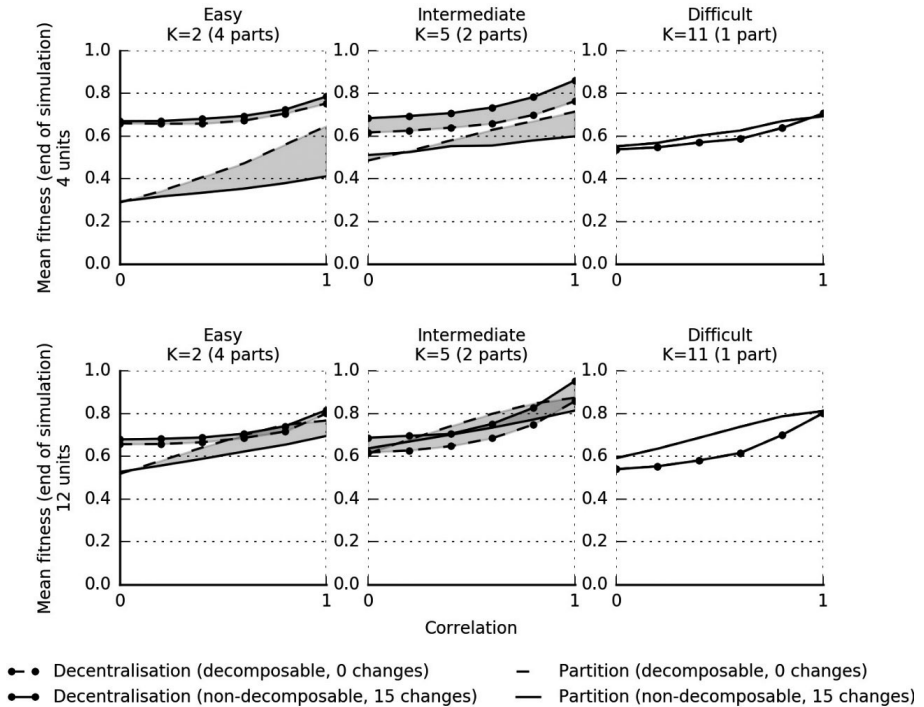


FIG. 5 – Simulation results of the decentralised and partition search strategies of organizations with 4 and 12 units. Mean fitness values are reported for 500 landscape simulations.

IV. A HEALTH CARE CASE STUDY OF THE PARTITION SEARCH STRATEGY: CHRONIC CARE MODEL

A case study involving wide scale health service renewal within a municipal primary care organization in Finland provides an example of the partition search strategy. This organization provides chronic and non-chronic healthcare services for a middle-sized Finnish city and its surrounding areas, comprising around 67,000 inhabitants.

This health care organization provides a good example of a multi-unit organization that faces heterogeneous demand across its different units. It comprises a “central unit” and seven smaller units known as “satellites”. The central unit serves a population of 27,000 citizens in the city centre. The satellite units serve smaller populations, of between 2,000 and 11,000 citizens. Three of the satellites are located in the suburbs, and four satellite units are located in rural areas.

In addition to the urban/rural distinction, the social environment and age demographics of the populations served by these different units varies significantly. Some units primarily serve a young population, dealing with issues such as substance abuse and mental health problems. Others primarily serve elderly citizens and their associated medical conditions.

There is a general trend within health care to new services that emphasize preventive care and the application of new digital technologies. Integrated care programs (Ouwens *et al.*, 2005), and the Chronic Care Model (Bodenheimer *et al.*, 2002) which these are based on, require radical changes in the internal organization structures of health care organization, and their external interactions with patients. It should be noted that the Chronic Care Model (CCM) does not specify exactly how system change should be configured within a particular context. Certain practices may be adopted from the general CCM framework, but an organization seeking to implement health care renewal still needs to experiment with alternative solutions and implement those which best suit its context.

The case organization had started to develop a new conceptual model in order to deal with key problems it had identified; namely, a reactive way of working, condition-centred view of service development, and a lack of cross-professional interaction. The renewal aimed to improve

both the availability of services to citizens and their health impact, as well as increasing productivity (i.e. reducing the resources required to treat each patient). The organization started to develop its own version of the Chronic Care Model. This was, in part, influenced by health care innovations developed and applied in other countries. However, the case organization also created new practical applications to meet its particular needs.

The development of a new operating model by this multi-unit organization highlights a number of the issues raised in the simulation model. First, there was much debate within management about the degree of autonomy that satellite units should have, and how much the innovation process should be coordinated by the central unit. On the one hand, it was acknowledged that local units typically have better knowledge of the local customers they serve. On the other hand, the central unit had greater access to resources and knowledge about the systemic renewal process.

A second issue highlighted by the case study is the recognition that some general elements of the Chronic Care Model would be suitable for all units of the organization, but that local, specific characteristics also needed to be taken into account. An example was provided by the development of new e-services. Elderly people did not necessarily have internet access or, if they did, limited experience, making the adoption of e-services difficult. Another example was the proposed segmentation of patients into two service groups, based on the need for either chronic or non-chronic care. The central unit developed this segmentation. However, smaller, satellite units found this segmentation to be unsuitable due to the health needs and demands of their local patient populations.

Another key issue was that of problem decomposition and the existence of links between modules/components. The Chronic Care Model is based on developing and using a set of core service components. These are: self-management support, clinical information systems, delivery system redesign, decision support, health care organization, and community resources (Bodenheimer *et al.*, 2002). These core components are not independent. There exist strong links between them, and an implementation of one component has a direct effect on the performance of other components. This means that redesign in one component requires adjustment and changes in the design of the other components.

Regarding the partition search strategy in particular, one aspect of the renewal in the case organization was the integration of previously independent operational entities, such as physical therapy and dental care with outpatient care. One of the satellite units piloted the integration of dental care services. As a result of this innovative activity, the unit became a leading service pioneer within the organization.

DISCUSSION AND CONCLUSIONS

In this paper, we have built a computational model of organizational search for a multi-unit organization and used the model to examine different forms of decentralised and centralised searches. The novelty of our model compared to earlier related studies (Kollman *et al.*, 2000; Chang and Harrington, 2000, 2003, 2004; Siggelkow and Levinthal, 2003) is that our model enables us to unpack “complexity” in order to distinguish between the effects of problem decomposability and demand heterogeneity.

The simulation results suggest that both decentralised and partition search strategies can outperform a centralised search when the landscapes between units are at least moderately heterogeneous. The relative performance of the centralised search, compared to decentralised search for example, depends on assumptions regarding the level of sophistication of the centralised search compared to that of localised search. The performance of decentralised search in our model highlights the power of parallel processing by multiple units. Given this set-up, the simulation results indicate that decentralised search is more effective where there is even a moderate degree of demand heterogeneity.

The results indicate that partition strategy is beneficial when the search problem is decomposable. When a high number of units is engaged in innovative search, the partition strategy can be beneficial in creating a large number of combinations of solutions that can be adopted by different units in a multi-unit organization.

Organizations implementing renewal processes are often facing conflicting demands in their task environments. Prior research on

ambidexterity (Raisch and Birkinshaw, 2008; Gibson and Birkinshaw, 2004) has focused on factors reconciling these tensions simultaneously. The general recommendation by scholars working on this topic is to separate units that are engaged in different markets (with different technological paradigms, and possibly at different stages of the industry life cycle) due to the different internal competences (supply side factors) required for businesses to successfully innovate and compete in different markets.

The findings of the simulation model, together with that of the case study, contributes to our understanding of the tensions that can arise from heterogeneous consumer demand. In the context of health care, heterogeneous demand is due to the different health needs of patients in different geographical areas, which are served by different units of the same organization. This affects organizational scale and scope, and requires an ambidextrous approach to innovation and organizational structures to support service innovation.

This opens up some new, potentially interesting avenues for empirical and simulation-based research in the field of service innovation. Existing research, focusing on the organization of service innovation activity, has hitherto mainly relied on qualitative case studies (Sundbo, 1996; Sørensen *et al.*, 2013). The theoretically driven research presented in this paper can be seen as an alternative way to address research into complex service innovations. Some research questions are difficult to explore using qualitative research methods only. In this paper, we have used a case study to illuminate the findings of a simulation model, and to open up further thinking about the ontology of strategic search options and practices.

Concerning innovation studies, some scholars have previously adopted a complex system view to innovation (e.g. Frenken, 2006). Yet there remains a predominant focus on technological drivers of innovation. Service innovations are in many cases complex entities that integrate technological and organizational practices, and new ways of producing value together with customers. We suggest there is considerable potential in using computational tools to better understand complex systems such as these⁵.

With regards to future development of the model presented here, future studies could examine in greater detail how a new system

5 There are some rare works, e.g. Desmarchelier *et al.* (2013) and Janssen (2015), who have used the characteristics-based frameworks of service innovation as a theoretical basis for formal modelling.

architecture or dominant design (Murmman and Frenken, 2006) is designed for service systems in the first place, and how this affects the different possible forms of local search which an organization chooses to use. For example, this may affect the cognitive heuristics that decision-makers use when engaging in search (cf. Gavetti and Levinthal, 2000). Another aspect not considered in the model, but which is clear from the case study, is the importance of competences and preferences (Windrum and García-Goñi, 2008) in the choice of search options.

Another aspect that has not been considered is the temporal complexity inherent in efforts at improvement over a long period of time (cf. Rahmandad, 2008; Denrell *et al.*, 2004). There is always uncertainty regarding how much a particular system configuration can yield benefits in the long term. Possible worse-before-better effects and limited resources for improvement can mean that even if a long term improvement solution exists, it may be difficult to implement in practice because of people's myopic understanding or limited resources for improvement (Repenning and Sterman, 2002; Morrison, 2012). One possible extension of our model is to take into account the resources needed for the search by each of the alternative strategies.

Finally, we have followed precedents by limiting the model scope to a single organization. Service innovations may involve a number of multi-unit organizations working in networks (De Vries, 2006). Future research could examine how different organizations can work together in order to design new/improved services. This entails relaxing an (implicit) assumption that there are no conflicting interests in the service development. This assumption is useful in order to focus on the information processing and communication aspects of an organization. When multiple organizations are working together, issues of motive alignment and trust are clearly relevant. This could either be examined using the transaction cost (cf. Colfer and Baldwin, 2010) or else a network governance (Jones *et al.*, 1997) perspective.

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REFERENCES

- BALDWIN C. Y.; CLARK K. B. (2006), "Modularity in the Design of Complex Engineering Systems", in BRAHA D.; MINAI A. A.; BAR-YAM Y. (eds.), *Complex Engineered Systems*, Berlin Heidelberg, Springer, p. 175–205.
- BENNER M. J.; TUSHMAN M. L. (2003), "Exploitation, Exploration, and Process Management: The Productivity Dilemma Revisited", *Academy of Management Review*, vol. 28, n° 2, p. 238–256.
- BODENHEIMER T.; WAGNER E. H.; GRUMBACH, K. (2002), "Improving Primary Care for Patients With Chronic Illness", *JAMA: The Journal of the American Medical Association*, vol. 288, n° 14, p. 1775–1779.
- CHAE B. (2012), "An evolutionary framework for service innovation: Insights of complexity theory for service science", *International Journal of Production Economics*, vol. 135, n° 2, p. 813–822.
- CHANG M.-H.; HARRINGTON, J. E. (2006), "Agent-Based Models of Organizations", in Tesfatsion, L.; Judd K. L. (eds.): *Handbook of computational economics, Volume 2*. Amsterdam, Elsevier. p. 1273–1337.
- CHANG M.-H.; HARRINGTON J. E. (2003), "Multimarket Competition, Consumer Search, and the Organizational Structure of Multiunit Firms", *Management Science*, vol. 49, n° 4, p. 541–552.
- CHANG M.-H.; HARRINGTON J. E. (2000), "Centralization vs. Decentralization in a Multi-Unit Organization: A Computational Model of a Retail Chain as a Multi-Agent Adaptive System", *Management Science*, vol. 46, n° 11, p. 1427–1440.
- CHANG M.-H.; HARRINGTON J. E. (2004), "Organization of Innovation in a Multi-unit Firm: Coordinating Adaptive Search on Multiple Rugged Landscapes", in BARNETT W.; DEISSENBERG C. and FEICHTINGER G. (eds.), *Economic Complexity*, Published Online, Emerald, p. 189–214.
- COLFER L.; BALDWIN C. Y. (2010), "The Mirroring Hypothesis: Theory, Evidence and Exceptions", Harvard Business School Working Paper 10-058.
- CSASZAR F. A. (2012), "Organizational structure as a determinant of performance: Evidence from mutual funds", *Strategic Management Journal*, vol. 33, n° 6, p. 611–632.
- DE VRIES E. J. (2006), "Innovation in services in networks of organizations and in the distribution of services", *Research Policy*, vol. 35, n° 7, p. 1037–1051.
- DENRELL J.; FANG C.; LEVINTHAL D. A. (2004), "From T-Mazes to Labyrinths: Learning from Model-Based Feedback", *Management Science*, vol. 50, n° 10, p. 1366–1378.

- DESMARCHELIER B.; DJELLAL F.; GALLOUJ F. (2013), "Environmental policies and eco-innovations by service firms: An agent-based model", *Technological Forecasting and Social Change*, vol. 80, n° 7, p. 1395–1408.
- DOBRAJSKA M.; BILLINGER S.; KARIM, S. (2015), "Delegation Within Hierarchies: How Information Allocation of Formal and Real Decision Authority", *Organization Science*, vol. 26, n° 3, p. 687–704.
- ETHIRAJ S. K.; LEVINTHAL D. (2004), "Modularity and Innovation in Complex Systems", *Management Science*, vol. 50, n° 2, p. 159–173.
- FRENKEN K. (2006), "Technological innovation and complexity theory", *Economics of Innovation and New Technology*, vol. 15, n° 2, p. 137–155.
- FRENKEN K.; NUVOLARI A. (2004), "The early development of the steam engine: an evolutionary interpretation using complexity theory", *Industrial and Corporate Change*, vol. 13, n° 2, p. 419–450.
- GALLOUJ F.; WEINSTEIN O. (1997), "Innovation in services", *Research Policy*, vol. 26, n° 4–5, p. 537–556.
- GANCO M.; HOETKER G. (2009), "NK Modeling Methodology in the Strategy Literature: Bounded Search on a Rugged Landscape", in BERGH D. D.; KETCHEN D. J. (eds.), *Research Methodology in Strategy and Management, Volume 5*. Published Online, Emerald Group Publishing Limited, p. 237–268.
- GAVETTI G.; LEVINTHAL D. (2000), "Looking Forward and Looking Backward: Cognitive and Experiential Search", *Administrative Science Quarterly*, vol. 45, n° 1, p. 113–137.
- GIBSON C. B.; BIRKINSHAW J. (2004), "The Antecedents, Consequences, and Mediating Role of Organizational Ambidexterity", *Academy of Management Journal*, vol. 47, n° 2, p. 209–226.
- JACOBIDES M. G. (2007), "The Inherent Limits of Organizational Structure and the Unfulfilled Role of Hierarchy: Lessons from a Near-War", *Organization Science*, vol. 18, n° 3, p. 455–477.
- JANSSEN M. J. (2015), *Service innovation in an evolutionary perspective*. Eindhoven: Technische Universiteit Eindhoven.
- JONES C.; HESTERLY W. S.; BORGATTI S. P. (1997), "A General Theory of Network Governance: Exchange Conditions and Social Mechanisms", *Academy of Management Review*, vol. 22, n° 4, p. 911–945.
- KAUFFMAN S. A. (1993), *The Origins of Order: Self Organization and Selection in Evolution*, Oxford, Oxford University Press.
- KOLLMAN K.; MILLER J. H.; PAGE S. E. (2000), "Decentralization and the search for policy solutions", *Journal of Law, Economics, & Organization*, vol. 16, n° 1, p. 102–128.
- LANGLOIS R. N.; ROBERTSON P. L. (1992), "Networks and innovation in a

- modular system: Lessons from the microcomputer and stereo component industries", *Research Policy*, vol. 21, n° 4, p. 297–313.
- LEVINTHAL D. A. (1997), "Adaptation on rugged landscapes", *Management Science*, vol. 43, n° 7, p. 934–950.
- LUOMA J. (2013), "Behavioral impediments to growing competitive activity: Insights from a longitudinal case study", Unpublished manuscript. Aalto University.
- MARCH G. J., (1991), "Exploration and Exploitation in Organizational Learning", *Organization Science*, vol. 2, n° 1, p. 71–87.
- MARENGO L.; DOSI G. (2005), "Division of labor, organizational coordination and market mechanisms in collective problem-solving", *Journal of Economic Behavior and Organization*, vol. 58, n° 2, p. 303–326.
- MORRISON B. J. (2012), "Process improvement dynamics under constrained resources: managing the work harder versus work smarter balance", *System Dynamics Review*, vol. 28, n° 4, p. 329–350.
- MURMANN J. P.; FRENKEN K. (2006), "Toward a systematic framework for research on dominant designs, technological innovations, and industrial change", *Research Policy*, vol. 35, n° 7, p. 925–952.
- NELSON R. R.; WINTER S. G. (1982), *An Evolutionary Theory of Economic Change*. Cambridge, Massachusetts: The Belknap Press of Harvard University Press.
- NICKERSON J. A.; ZENGER T. R. (2004), "A Knowledge-Based Theory of the Firm –The Problem-Solving Perspective", *Organization Science*, vol. 15, n° 6, p. 617–632.
- OUWENS M.; WOLLERSHEIM H.; HERMENS R.; HULSCHER M.; GROL R. (2005), "Integrated care programmes for chronically ill patients: a review of systematic reviews", *International Journal for Quality in Health Care*, vol. 17, n° 2, p. 141–146.
- RAHMANDAD H. (2012), "Impact of Growth Opportunities and Competition on Firm-Level Capability Development Trade-offs", *Organization Science*, vol. 23, n° 1, p. 138–154.
- RAHMANDAD H. (2008), "Effect of Delays on Complexity of Organizational Learning", *Management Science*, vol. 54, n° 7, p. 1297–1312.
- RAISCH S.; BIRKINSHAW J. (2008), "Organizational Ambidexterity: Antecedents, Outcomes, and Moderators", *Journal of Management*, vol. 34, n° 3, p. 375–409.
- REPENNING N. P.; STERMAN J. D. (2002), "Capability traps and self-confirming attribution errors in the dynamics of process improvement", *Administrative Science Quarterly*, vol. 47, n° 2, p. 265–295.
- RIVKIN J. W.; SIGGELKOW N. (2003), "Balancing Search and Stability: Interdependencies among Elements of Organizational Design", *Management Science*, vol. 49, n° 3, p. 290–311.

- SAH R. K.; STIGLITZ J. E. (1986), "The Architecture of Economic Systems: Hierarchies and Polyarchies", *American Economic Review*, vol. 76, n° 4, p. 716–727.
- SIGGELKOW N.; LEVINTHAL D. A. (2003), "Temporarily Divide to Conquer: Centralized, Decentralized, and Reintegrated Organizational Approaches to Exploration and Adaptation", *Organization Science*, vol. 14, n° 6, p. 650–669.
- SIGGELKOW N.; RIVKIN J. W. (2006), "When exploration backfires: Unintended consequences of multilevel organizational search", *Academy of Management Journal*, vol. 49, n° 4, p. 779–795.
- SUNDBO J. (1996), "The balancing of empowerment", *Technovation*, vol. 16, n° 8, p. 397–409.
- SØRENSEN F.; SUNDBO J.; MATTSSON J. (2013), "Organisational conditions for service encounter-based innovation", *Research Policy*, vol. 42, n° 8, p. 1446–1456.
- WILLIAMSON O. E. (1985), *The Economic Institutions of Capitalism*, New York, NY, Free Press.
- WINDRUM P.; GARCÍA-GOÑI M. (2008), "A neo-Schumpeterian model of health services innovation", *Research Policy*, vol. 37, n° 4, p. 649–672.

APPENDIX

1. MODEL EQUATIONS

The fitness landscape for each unit is calculated as a weighted average of the fitness values of a joint fitness landscape component of all units $\pi(x, N, K)$ and a unique fitness landscape component of each unit $\pi'(x, N, K, o)$:

$$f(x, N, K) = (1 - w) \cdot \pi(x, N, K) + w \cdot \pi'(x, N, K, o) \quad (1)$$

Parameter w determines the demand heterogeneity between the different organizational units. For $w=0$ the fitness landscapes are identical and for $w=1$ the fitness landscapes of the different units are completely uncorrelated.

Fitness values $\pi(x, N, K)$ and $\pi'(x, N, K, o)$ are created by drawing i.i.d. random numbers from a normal distribution:

$$\pi_i(x, N, K) \sim N\left(0, \frac{1}{w^2 + (1-w)^2}\right) \quad (2)$$

$$\pi'_i(x, N, K, o) \sim N\left(0, \frac{1}{w^2 + (1-w)^2}\right) \quad (3)$$

The variance of a weighted sum of two random numbers has the property $\sigma^2_{wX_1 + (1-w)X_2} = w^2 \sigma_{X_1}^2 + (1-w)^2 \sigma_{X_2}^2$. From this it follows that the ratio of the variance of a single landscape alone to the variance of a weighted sum of the two i.i.d. landscapes is $\frac{1}{w^2 + (1-w)^2}$. We draw the random fitness values from a normal distribution that depends on w , with the result that the variance of the weighted average does not depend on w . This allows us to compare the search on different landscapes (increasing the variance of the landscape would increase the maximum fitness payoffs on the landscape and thus affect the search results).

2. CORRELATION BETWEEN FITNESS LANDSCAPES OF DIFFERENT UNITS

The mean values are identical: $(\mu_{Y_1} = \mu_{Y_2} = \mu_X = \mu)$

The variance of a weighted average Y depends on w :

$$\begin{aligned}
\sigma^2_Y &= \sigma^2_{wX_1+(1-w)X_2} = w^2 \sigma_{X_1}^2 + (1-w)^2 \sigma_{X_2}^2 = \sigma_X^2(w^2 + (1-w)^2) \\
\Rightarrow \rho_{Y_1, Y_2} &= \frac{E[(Y_1 - \mu_{Y_1})(Y_2 - \mu_{Y_2})]}{\sigma_{Y_1} \sigma_{Y_2}} \\
&= \frac{E[((1-w)X_1 + wX_2 - \mu) \cdot ((1-w)X_1 + wX_3 - \mu)]}{\sigma_X^2(w^2 + (1-w)^2)} \\
&= \frac{E[((1-w)X_1 + wX_2)((1-w)X_1 + wX_3) - ((1-w)X_1 + wX_2)\mu - ((1-w)X_1 + wX_3)\mu + \mu^2]}{\sigma_X^2(w^2 + (1-w)^2)} \\
&= \frac{(1-w)^2 E[X_1^2] + w(1-w)E[X_1X_3] + w(1-w)E[X_1X_2] + w^2 E[X_2X_3] - \mu(2(1-w)E[X_1] + wE[X_2] + wE[X_3]) + \mu^2}{\sigma_X^2(w^2 + (1-w)^2)}
\end{aligned}$$

Because X_1, X_2, X_3 are independent, $E[X^2] = \sigma_X^2 + \mu_X^2$ and $E[X_1X_2] = E[X_1X_3] = E[X_2X_3] = E[X_1]E[X_2] = \mu^2$

$$\Rightarrow \rho_{Y_1, Y_2} = \frac{(1-w)^2(\sigma_X^2 + \mu_X^2) + 2w(1-w)\mu^2 + w^2\mu^2 - \mu(2(1-w)\mu + 2w\mu) + \mu^2}{\sigma_X^2(w^2 + (1-w)^2)} = \frac{(1-w)^2\sigma_X^2 + 0 \cdot \mu^2}{\sigma_X^2(w^2 + (1-w)^2)} = \frac{(1-w)^2}{w^2 + (1-w)^2}$$

The simulation experiments were run for evenly spaced values of the correlation. In order to do this, the equation for the correlation above was solved for w (using Mathematica):

$$w = \frac{\rho_{Y_1, Y_2}^{-1} + \sqrt{\rho_{Y_1, Y_2}^2 - \rho_{Y_1, Y_2}^2}}{2\rho_{Y_1, Y_2} - 1}$$