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The sensing paradox in service innovation: Too much user-producer interaction?

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Abstract

This study seeks to explain the paradox that firms most engaged in fulfilling actual user needs might be the ones who benefit less from a capability for systematically evaluating market demands. Service-oriented innovation research stresses that the relational nature of service delivery, especially when customized, provides opportunities for firms to engage in intensive user-producer interaction already during their regular business activities. We examine under which conditions having a strong sensing user needs capability can be a weakness rather than a strength for such firms.
By using NK-logic, we modelled the conjunction of customer and firm behaviour with respect to sending and sensing user feedback. Our simulations resulted in a hypothesis regarding the relation between various interactive search strategies on the one hand, and innovativeness on the other hand. Subsequently, we used survey data from 292 respondents to verify these findings empirically.
Our regression results suggest that, for firms who provide client-specific services, there is limited value in investing in an ability to monitor and evaluate user feedback closely. Having a sensing capability and receiving user requests has a negative interaction effect for firms providing customized solutions, while this effect is positive when firms do not tailor their services. The results confirm that focusing too much on articulated market demands might prevent customizing

firms from introducing commercially successful service solutions. With these findings, we support innovation managers dealing with the strategic dilemma whether or not to devote resources to sensing capabilities.

Jelcodes:D83,L84

1. Introduction

In many respects, the innovation landscape firms are facing today is changing rapidly. One notable trend, sometimes even referred to as paradigm shift, is the adoption of innovation modes characterized by a high level of openness (Laursen and Salter, 2006; Baldwin and Von Hippel, 2011). Perhaps the most important form of openness concerns learning by engaging in user-producer interaction (Lundvall, 1988; Chatterji and Fabrizio, 2014). Especially in the context of manufacturing industries, traditionally adhering to 'closed' innovation processes, intensification of reliance on customer signals is strongly advocated (Chesbrough, 2006). In order to access and process potentially valuable feedback, firms are encouraged to develop sensing user needs capabilities (Teece, 2007; Den Hertog et al., 2010). Maybe more than ever, strong sensing capabilities are believed to be crucial for a modern firm to stay adaptive (Bharadwaj and Dong, 2013).

A second major development, albeit taking place less disruptively, pertains to the ongoing service revolution (Bell, 1973). During especially the second part of the previous century, advanced economies started to concentrate on the provision of services rather than physical goods (Gallouj and Djellal, 2010). To escape the commodity trap, also 'servitizing' manufacturing firms have started to switch to service-oriented business models (Chesbrough, 2011; Bowen et al., 1991). Following a service-dominant logic, they recognize the opportunities of adding value by delivering services that meet the actual needs of customers better than providing them with material artefacts (Vargo and Lusch, 2004; Suarez et al., 2013). This trend has important implications for how firms give shape to their innovation efforts, including their use of external knowledge (Mina et al., 2014).

A key characteristic of service delivery is found in the intense interaction with customers. Contrary to the traditional production mode, in which manufacturing firms produced artefacts ultimately sold by retailers, the production of service propositions brings firms in permanent contact with their clients (Anderson et al., 1997). This is particularly the case when firms strive to add value by customizing their services to the specific needs of their customers (Bowen and Ford, 2002). Fulfilling these demands provides firms with rich user feedback on unmet market needs, as well as on the quality of the created solution. According to a large body of evidence, user interaction related to service delivery therefore forms a key input for new service development (Edvardsson et al., 2012).

This paper focuses at the point where the two developments coincide. While the opportunities of using user knowledge might motivate firms to invest in building a strong sensing capability, the very shift to service-oriented business models appears to provide already a natural way for acquiring ideas on what propositions to develop next. The inherent openness of customized service delivery begs the question to what extent having such a capability has sufficient additional value for innovation-pursuing service providers. Particularly concerning is the claim that intensive forms of user-producer interaction might give firms an overly strong focus on the needs of existing clients, thereby leading them to neglect opportunities for developing solutions with a larger market potential (Christensen, 1997; Laursen, 2011). Survey-analyses like the one by Mina et al. (2014) indicate that if business services and service-integrated manufactures source actively, attention is focused on science and technology rather than on market knowledge. A paradoxical finding, if one accepts that fulfilling user needs lies at the heart of what 'to serve' really means.

In order to examine the contested value of actively sourcing user demands, we commence with reviewing existing research on firm and user behaviour related to sensing and signalling user needs. Since innovation literature is largely biased towards manufacturing, the role of user requests is often studied in the context of full-fledged user innovations (Von Hippel, 1976) or user involvement in co-creation experiments (Magnusson et al., 2003). Such a perspective neglects that service-oriented research requires attention for the knowledge flows that occur when firms are practically permanently exposed to user feedback, absent any user participation threshold (Dahlander and Piezunka, 2014).

As the debate on sourcing user knowledge for innovation suffers from a lack of theory (Chatterji and Fabrizio, 2014), also the merits of various modes of user-producer interaction remain largely unknown. To fill this gap, we develop a formal model for the mechanisms determining the value of user knowledge in search processes. Following the logic of NK (Kauffman, 1993), we specify four basic types of interactive search strategies used for exploring new offerings. The model and corresponding simulations lead us to formulate a verifiable hypothesis. We use survey data from 292 respondents to test empirically to what extent sensing and user input are related to sales derived from new services.

Our regression results suggest that, for firms frequently confronted with user requests, there is some value in developing a capability for systematically monitoring and evaluating user needs. However, we also observe that the importance of this capability is limited. Having a strong sensing capability and receiving a high degree of user feedback has a negative interaction effect for firms providing customized services, but a positive interaction effect when firms only deliver non-tailored services. These results thereby contextualize the hypothesis that focusing too much on articulated user needs might prevent firms from introducing successful service solutions.

With our findings, we support innovation managers dealing with the strategic dilemma whether or not to devote resources to sense user needs. While non-customizing service providers appear to benefit from developing strong sensing capabilities, this seems to be less the case for firms who might get trapped in suboptimal solutions as they fulfil the requests of individual customers.

2. Literature review

2.1. User feedback as a source of variation

In the burgeoning literature on openness and innovation sources, the role of users is a highly prominent topic (West et al., 2014). Knowledge stemming from the actual use of products is valuable to organizations seeking how to renew or improve their offerings and firm performance. When it comes to understanding and identifying new market needs, as well as optimizing existing products, users themselves are often better positioned than firms (Bogers et al., 2010). By incorporating user-based knowledge (e.g. suggestions on what improvements to make), firms can direct their search efforts towards further elaboration and large-scale commercialization of fruitful user ideas (Chatterji and Fabrizio, 2012; 2014). However, because information is ‘sticky’, signals on user needs can only be acquired through intensive user-producer interaction (Von Hippel, 1994; Lundvall, 1988)

Acknowledging the importance of users own visions on their demands has led innovation scholars to shift from a producer-focus to a user-focused paradigm (Baldwin and Von Hippel, 2011). Those few innovation studies addressing services largely follow the same line of reasoning. Oliveira and Von Hipppel (2010), for instance, show how many commercial and retail banking services were originally developed by non-bank firms. On this basis, the authors claim that also in services a user-centred perspective on innovation is appropriate: apart from relying on service providers, customers can also ‘serve’ themselves in novel ways.

The demonstrated approach for extending research on user knowledge (regarding their needs) to services follows an assimilation approach, in which the domains of manufacturing and services are regarded as fundamentally equal (Coombs and Miles, 2000). A different perspective on the role of users in service innovation is offered by studies from predominantly marketing, operations management and innovation studies. Following demarcation and synthesis schools of thought, these literatures typically highlight or integrate service-specific aspects in innovation theory (Drejer, 2004; Miles, 2007). One such aspect concerns the way firms meet the demands of their customers. Whereas manufacturers typically develop physical artefacts with which customers can fulfil their own needs, the provision of tailored services does not (only) go through such intermediary objects: by definition, service providers directly deliver the desired solution or experience itself (Pine and Gilmore, 1999; Den Hertog et al., 2010).

Meeting the requests of individual clients requires knowledge that only can be obtained through intensive customer interaction (Matthing et al., 2004). Service delivery is often understood as an interactive process in which a provider and a consumer jointly aim to fulfil the consumers’ needs (Vargo and Lusch, 2004). To what extent they succeed is determined by how well both parties align their resources and competences in this act of co-creation (Vargo and Lusch, 2008). This implies that, apart from being able to express their needs accurately, consumers also need to be involved in subsequent phases of service production. The quality of an expert consult, for instance, highly depends on how the user phrases its question as well as on how the issued advises will be used.

In their dual position of consumer and co-producer, the clients of a service firm are able to provide valuable feedback on the solution or experience they have been purchasing. According to Rubalcaba et al. (2012, p. 702), innovation-pursuing “service firms can benefit from their advantage over manufacturing firms, which stems from their personnel’s direct interactions with customers”. Similarly, Cusumano et al. (2014, p. 5) state that “because some services are grounded within actual consumer-producer interactions, they reveal information about consumption and usage”. Thus, although service providers tend to rely heavily on tacit knowledge, which is more difficult to transfer than codified knowledge like technological characteristics, stickiness of information might be relatively less of an issue in services. Ultimately, the customer-oriented and relational nature of service provision renders the distinction between producer-focused versus consumer-focused innovation paradigms irrelevant.

Service consumers continuously express signals during the simultaneous processes of (co-) production and consumption, which is why service firms have an alternative to setting up resource-consuming co-creation practices (Rubalcaba et al., 2012). When it comes to the content of real-action communication flows, feedback can vary in its level of detail (Gustafsson et al., 2012).

First, users can implicitly or explicitly signal to what extent they are satisfied with the service that is being delivered to them and whether it meets their needs (Matthing et al., 2004). Of particular interest is that service consumers can communicate their appreciation or frustrations during the very acts of coproduction and consumption (Gustaffson et al., 2012), instead of having to do an effort by searching and filling out complaint forms, going back to the shop, etcetera. The interactive nature of service provision allows clients to express evaluative signals immediately to the (front-office employees of) the organization they are dealing with. Apart from being more direct, such interaction also provides opportunities for users to express in detail what particular aspect of a service is satisfying or dissatisfying them. These signals, respectively, can support decisions whether to maintain or alter the properties of the provided service. Especially complaints about a certain feature might provide incentives to search for alternative ways to deliver a solution or experience.

By explicitly formulating a demand for new services, users sometimes go even further in informing a service provider about the needs they would like to see fulfilled. When reviewing research on users as a source of innovation-related knowledge, Bogers et al. (2010) state that information about unmet user needs is likely to go along with suggestions on how to address it. Suggestions from external partners, including customers, are nowadays a popular topic of study (Dahlander and Piezunka, 2014). Also in the context of services, customers coming forward with a specific need often are found to provide cues for a possible way to solve it: "expressed needs may have either expressed or latent solutions" (Gustafsson et al., 2012, p. 313). By tailoring services to the specific needs of a customer, service providers continuously experiment with new ad hoc solutions that can possibly scaled up to other users as well (Drejer, 2004; Toivonen and Tuominen, 2009). As a result, service professionals not only obtain inspiring in-depth insights in a customer's use-situation, but being directly confronted with users' perceptions of problems and unmet needs often also yields ideas for which improvements to make (Rubalcaba et al., 2012). It is at this point that the distinction between coproduction and co-innovation starts to blur, thereby making Von Hippel's notion of distributed innovation a common term in service innovation literature (Den Hertog, 2000).

In the light of search for innovative solutions, it should be noted that user demands and suggestions are particularly valuable because of being original, timely and comprehensive (Bogers et al., 2010). However, unless uttered in collaborative development projects and deliberate co-creation experiments (which fall beyond the scope of this study), user input often is fragmentary, less producible and unelaborated (Magnusson et al., 2003). Knowledge stemming from personal use experience tends to be specific for individual needs – latent or articulated –, and therefore only covers a limited part of the body of knowledge required for implementing a total solution (Riggs and Von Hippel, 1994; Sandulli, 2013). The above-mentioned forms of feedback thus pertain mostly to evaluations and suggestions for particular aspects of a service: it remains up to the service provider how to use this knowledge for improving the entire service as such (Vargo and Lusch, 2008).

2.2. Organizational capabilities for sensing user needs

Recognition of the importance of user demands begs the question how firms can make strategic use of it. Again, the interest in services corresponds with a (slightly) different focus than the research stemming from a predominantly manufacturing context. The latter, to start with, has typically been examining how producer firms can cross the boundary between their firm and the users of their products. Such efforts are particularly focused at locating, screening and transferring need-related knowledge from the user to the producer (Bogers et al., 2010; Von Hippel, 1994).

In the context of customizing service providers, the distance to users is smaller than for firms that exclusively produce and sell physical and standardized goods. However, given that tailored service delivery essentially pertains to fulfilling user's actual needs rather than providing them an intermediary artefact, it seems all the more important for firms to keep track of present and latent desires. Here, we are mainly interested in the characteristic that service providers are continuously exposed to some sort of feedback, but have to decide how they deal with this. Studies on user involvement suggest that the best way for acquiring user knowledge is by interacting with them 'insitu' rather than by inviting them to participate in experimental settings (Edvardsson et al, 2012).

In order to understand the needs expressed by customers, organizations deploy activities that help them to gather and evaluate the signals they are confronted with. According to Matthing et al. (2004), service firms can respond aptly to user needs by engaging in learning processes. Specifically, the authors refer to the linked processes of market sensing and sense making as proposed by Day (2002). Whereas the first aspect concerns the systemic collection of information, the second type of sensing pertains to interpreting and evaluating the accumulated knowledge (Matthing et al., 2004).

Drawing upon these insights, Den Hertog et al., (2010) introduced sensing user needs as an essential dynamic capability for realizing innovation specifically also in a services context. Being a dynamic capability (Teece et al., 1997), the strength of a firm's ability to sense user needs depends on whether it has structured (but not necessarily formalized) routines in place for staying aware of what its clients want. Although firms can differ in how they fulfil these routines, as indicated by the notion of micro-foundations, there is general agreement that higher-order capabilities can be compared across firms (Eisenhardt and Martin, 2000; Teece, 2007). Such a comparison can point at different capability levels or strengths.

Most service firms have to some extent an intelligence function for keeping track of what existing or potential customers want (Den Hertog et al., 2010). Since accessing user input might to a large extent be performed via a service firm's routine-based interaction with its customers, an important part of the value of sensing user needs lies in carefully administering and systematically evaluating feedback. Creating an overview of which comments are expressed most often and most urgently gives firms an impression of what aspect(s) of their offerings to improve. Deploying such market sensing activities (Day, 2002) thus offers firms an account of where to concentrate efforts: the sensed feedback can provide inspiration when experimenting with new concepts, or allows firms to adjust the novel solutions they had in mind already.

When firms assign particularly high priority to customer demands, they might invest more substantially in developing their sensing user needs capability. Firms deploying a wide range of advanced sensing practices arrive at a point where users play a truly central role in the search for better propositions: user-knowledge is than treated as a key input in the process of sense making (Day, 2002). A strongly developed sensing capability allows firms to determine exactly what their users really want and to focus their resources on fulfilling the most urgent user needs.

2.3. The contested value of listening to users

The transfer of user knowledge is essentially a matter of sending and receiving information. While studies on openness in manufacturing typically appear to focus on bridging the distance between firms and users, research on service provision requires a different scope. Especially when solutions are customized to the needs of individual customers, firms are exposed to real-action knowledge flows which might contain valuable information. The question then becomes how to respond to these flows.

By discriminating low and high levels of both sensing and sending activities, we identify four typical modes of user-producer interaction (see Figure 1). As for the behaviour of users: feedback originating from direct interaction can tell a service provider in the first place that something needs to be changed and on what aspect, as indicated by expressions of (dis)satisfaction and signals of unfulfilled needs. If users provide a higher degree of feedback, their demands can also give an indication of how this can be done best, i.e. which changes are thought to be most suitable. Users who frequently express their requests provide information that is more like concrete suggestions rather than only complaints. Firms, on their turn, can obtain inspiration for innovative solutions by (only) monitoring how their customers are using and experiencing provided services. Or, when investing more substantially in their sensing capability, they can take the user-centric approach in which they follow their users closely in order to be able to adjust and optimize their services precisely to the spotted needs.

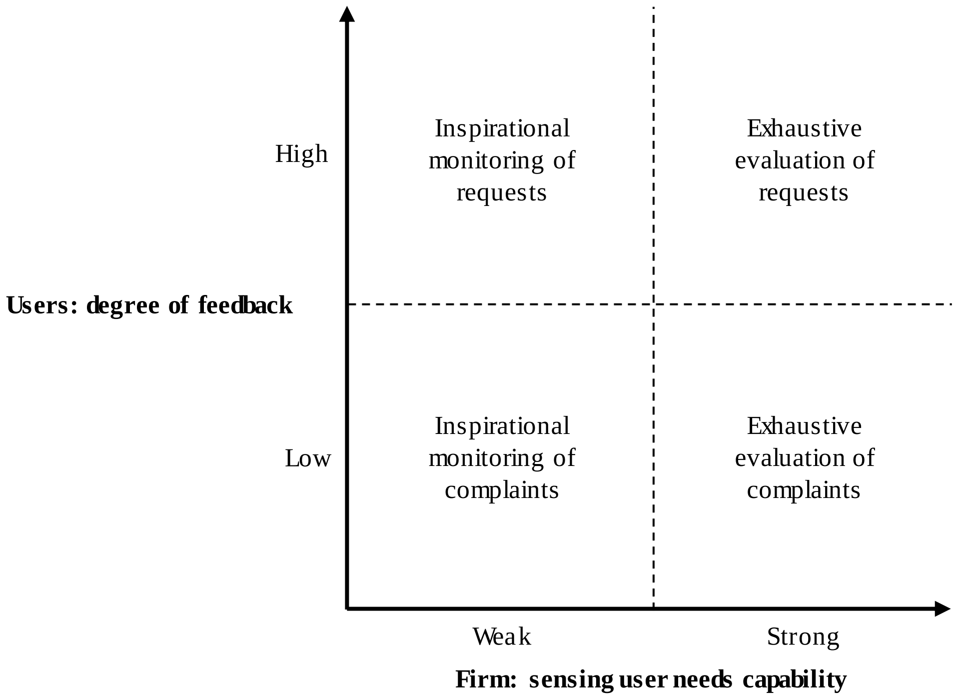


Figure 1: Four modes of user-producer interaction

Deciding whether to invest resources in sensing requires insight in the respective advantages of each interaction mode, including the conditions under which these advantages are most prominent. Despite widespread academic interest in both user innovation and service innovation, however, there is a scarcity of research asking to what extent user's communicativeness and active sensing affect each other's role in innovation processes. In a service-oriented study, Salunke et al. (2013, p. 1093) state that "the use of dynamic capabilities in gaining and exploiting customer-based knowledge and its effect on sustaining innovation-based advantage remains a neglected area". Also Gallouj and Djellal (2010) contend that the role of customers in service innovation is still a conceptual and empirical gap.

On the one hand, we noted that insight in user needs is believed to be crucial for finding new ways to serve them. Studies on the interactive nature of service delivery have shown that the daily and intense confrontation with users indeed forms an important source of inspiration for the development of new service solutions (Bryson et al., 2012; Kristensson, 2004). For instance, survey research based on the Oslo manual (OECD, 2005b) revealed that the more firms are exposed to user interaction, the better they perform in generating innovative solutions (Leiponen, 2005; Tether, 2005). Likewise, Love et al. (2011) show that the importance of user interaction is especially prominent in the exploratory phase of the innovation value chain. These findings suggest that service providers might benefit from strengthening their ability to capture and assimilate external knowledge.

On the other hand, ever-more attention for user needs is perhaps not per se beneficial for innovation success. While current students of openness in innovation increasingly examine the issue of costs and downsides of knowledge sourcing (Dahlander and Piezunka, 2014; Laursen and Salter, 2006), scholars have been warning already for several decades that listening too carefully to users might have an adverse effect. In line with Rosenberg's notion of user needs as a focusing device (1969), Hamel and Prahalad (1991) and Christensen and Bower (1996) conjectured that knowledge about the demands of the existing user base can strongly narrow the options a firm is willing to explore. As existing customers can exert more influence than then potential customers, a firm can be held captive by its current client base and only 'search for new solutions along established paths' (Laursen, 2011). The consequence is that especially incumbent firms might fail to identify propositions that could serve a larger market (Christensen, 1997). Despite the fact that this tension is known to many innovation scholars, only few empirical studies have investigated whether intensive user-producer interaction truly increases the chance that firms yield innovations Lundvall would qualify as 'unsatisfactory' (1988). According to a recent survey study by Laursen (2011), firms relying strongly on input from their users do at some point experience negative returns with respect to their innovative performance. Whether this depends on the types of services (or goods) a firm develops is left to future research, just like questions related to the number and behaviour of clients.

There are reasons to believe that the caveat underlying the innovator's dilemma (Christensen, 1997) is all the more present when firms tailor their services to the needs of customers with whom they engage in co-production. In such circumstances, firms might devote most of their attention and resources to the development of client-specific solutions. These ad hoc inventions only become successful innovations when they are also commercialized in other contexts (Drejer, 2004). Because transferring tacit concepts to other clients is observed to be highly difficult (Toivonen and Tuominen, 2009), there is a substantial risk that customizing service providers relying heavily on their sensing user needs capability ultimately fail to introduce solutions that meet widely shared market demands.

In sum, existing research is inconclusive with respect to the question which interaction mode is relatively most effective for realizing successful innovation. It therefore also remains unclear whether service providing firms really should develop a sensing user needs capability. This is what we will assess in the remainder of this paper. Instead of directly formulating two opposed hypotheses or hypothesizing a curvilinear relationship between user feedback and sensing, we choose to explore deeper the mechanisms determining when exactly adverse effects can occur.

3. Simulating different modes of user-producer interaction

3.1. Evolutionary search according to NK logic

Assessing the relative benefits of the distinct interaction modes requires a theoretically grounded understanding of innovation dynamics. To this goal, we draw upon evolutionary theorizing on technological and economic change (Nelson and Winter, 1982). This school of thought provides a rich basis of theory and methods for inquiry into the mechanisms behind novelty creation. Here, we are particularly interested in strategies regarding variety generation and selection.

In an evolutionary interpretation, the development of new offerings can be regarded as an experimental search process marked by uncertainty (Fleming, 2001). Firms try to improve the fitness of a product by modifying one or more of the elements it is composed of (Frenken, 2006). For instance, when trying to improve a bicycle, one can think of modifying its frame, gears or brakes. Possible design options for the latter dimension are handbrakes and coaster brakes. The outcome of introducing a modification is often uncertain: even if there are indications that a change will improve the 'technical' quality of a product, it remains difficult to estimate how the market will react to it (i.e. the 'evolutionary fitness' of the overall product). What is more, modification of one product dimension might have impact on the functionality of other elements. An apparent improvement in one aspect of a product might therefore lead to an overall fitness reduction (Beinhocker, 2006).

Borrowing from biological science, the evolutionary school of thinking proposed a form of complexity theory to investigate the above-mentioned characteristics of innovation processes. According to Kauffman's (1993) NK-logic, the act of innovation corresponds with search in multidimensional design spaces. Firms can pursue better solutions by changing the design options ('alleles') of one or more of those dimensions. The number of elements or dimensions a design space is composed of is denoted by the parameter N, while K expresses the number of interdependencies between them. When such interdependencies are entirely absent (K = 0), a mutation in one dimension will not affect the fitness of any other part of the design space that is being explored. In the long run, experimentation can be expected to identify which combination of dimensions delivers the highest fitness. The extreme opposite of a smooth fitness landscape is a rugged one (Levinthal, 1997), in which interdependencies between all dimensions exist (K = N-1). The 'peaks' in such a landscape are formed by design configurations in which changing one individual element will no longer result in a higher fitness: only by making larger leaps (modifying multiple dimensions simultaneously), firms can try to reach higher local optima or even the global optimum of the fitness landscape in question.

In the subsequent sections, we combine NK-logic with findings from service innovation literature to specify how we can formalize the intersection of key dynamics related to the following question: How important exactly is it to have a sensing user needs capability when the provision of customized services continuously confronts a firm with user input?

3.2. Design space of services

As we stressed in our literature review, the conjunction of sensing behaviour (by firms) and sending behaviour (by users) is of particular interest in the context of customized services. First, because service consumers tend to participate in the production of the final experience, they have ample opportunities for expressing their needs and satisfaction with the service that is being delivered. This co-produced nature of a firms' output, and especially the knowledge flows that stem from it, challenges the necessity for innovation processes to rely on the input stemming from internal sensing capabilities. A second and related reason to focus at services is that, compared to manufacturers, service providers invest less in R&D (Miles, 2007). This tendency to rely not or less on internal departments for generating new ideas implies a relatively high dependence on external signals, regardless whether they are obtained actively or passively.

Applying NK-logic in the context of services is a not straightforward exercise: defining the dimensions of a product is challenging when it is essentially intangible (Nelson and Winter, 1982; Frenken, 2006). Earlier contributions in the field of strategic management have studied particular services, like airlines, by regarding them as systems of interrelated activities (Porter and Siggelkow, 2008). More recently, scholars started to use this approach for analysing a greater variety of service solutions (Chae, 2012a, 2012b; Desmarchelier et al., 2013). Particularly promising in this respect are the opportunities offered by conceptualizing services on the basis of multiple distinct dimensions. In 2000, Den Hertog introduced a four-dimensional framework for describing where novelty in services can occur. After becoming widely adopted (Droege et al., 2009; Rubalcaba et al., 2012), the original framework was recently extended with two more dimensions (Den Hertog et al., 2010). Accordingly, novelty in services can concern changes in the following six dimensions: the service concept, the customer relation, the value system (business partners), the revenue model, the organizational delivery system, and the technological delivery system.

The multidimensional approach to describing services provides a fruitful basis for application of NK-logic to any type of solution or experience that is being produced. In this interpretation, firms develop new services by aligning changes in one or more of the dimensions. Various authors, to start with Gallouj and Weinstein (1997), have noted that changes in one dimension might often require modifications in other dimensions as well. This can be explained by the fact that a change in one dimension is relatively unlikely to yield success (either the focal firm or its competitors would have tried this incremental change). Secondly, and more importantly, interdependencies in the design space might offset the success of a single mutation. In order to make a novel service a success, it is likely that some other dimensions need to be adapted as well. Reasoning from this explanation, we assume a rather average degree of mutual interdependence ($K = 2$ or $K = 3$) when defining a service design space on the basis of the six-dimensional framework ($N = 6$) by den Hertog et al. (2010). This assumption, in which K is neither zero nor maximal, is consistent with empirical applications of the NK-logic in a non-service context (Simon, 2002).

3.3. Translating interaction modes into search strategies

Although both sending and receiving user requests (individually) are often found to be beneficial for innovation success, few scholars examined the conjunction of the two.

In section 2, we identified four typical behavioural modes for users and firms. Each of the quadrants in Figure 1 essentially corresponds with a different way of searching through a multidimensional design space. The proposed interaction modes can be used for simulating how the different combinations of user and firm behaviour affect innovativeness and firm performance. Before clarifying how the respective ‘search strategies’ can be modelled (Figure 2), we repeat that users have predominantly insights in their needs and not so much in how to deliver an entire solution. On this basis we assume that if they provide feedback they do this only on specific product aspects rather than that they provide full-fledged plans for the delivery of a new service. For the sake of simplicity of our formal model, we assume that each firm delivers one single service that yields only one type of feedback. We also assume that firms innovate by altering only one dimension per move.

The four search strategies corresponding with the 2*2 interaction modes can be modelled according to Function 1, which expresses the chance (P) that a firm will mutate by selecting allele q on dimension n. This probability is determined by the attractiveness of that particular position in the landscape ($X_{n,q}$). In Appendix F we describe how the attractiveness of a certain allele n on dimension q is a function of the fitness of that allele ($w_{n,q}$) and of the alleles in the dimensions that are related, if interdependencies are present. Essentially, the chance that a certain position gets selected is a matter of the ratio between the attractiveness of that mutation versus the sum of the attractiveness values of all alternative mutations. Therefore, $\sum_q P = 1$. Note that this summation pertains to all possible positions in the landscape, which is the product of the number of dimensions (N) and the number of alleles per dimension (Q, for all n). Finally, argument β in $X_{n,q}(\beta)$ stands for the type of feedback obtained from users, and exponent α relates to the two ways firms can deal with this feedback.

Function 1: $P_{n,q} = \frac{X_{n,q}(\beta)^{\alpha}}{\sum_q^{N*Q} X_{n,q}(\beta)^{\alpha}}$

The feedback β that user provide, determining the attractiveness of a certain mutation ($X_{n,q}$) can take two different forms. In case users do not or hardly take action to express their requests, it is likely firms only can obtain information about (dis)satisfaction (i.e. compliments or complaints on a particular aspect of the service solution). In our formal model we assume that the worst dimension of a service is the most attractive one to be manipulated, while praised dimensions should remain unaffected. This occurs when $X_{n,q}$ equals the distance between the maximum fitness of a certain dimension and the fitness of the currently chosen allele at that dimension ($w_{n,q(now)}$). Indeed, the perceived attractiveness of making a mutation still only depends on undetailed information: firms with this type of user feedback can observe which dimension has the weakest fitness at a given moment, but will have to choose a new allele on that dimension themselves. We assume they do this at random.

When users do express their requests more intensively, they can also convey information about how much they would appreciate a certain modification q on dimension n. Because customizing service providers will tailor their service to this particular need, they can obtain an indication of the fitness value of a dimension n when changing the current allele into the suggested allele. Although this information appears very rich, it still only pertains to the fitness at the level of individual dimensions. As stated before, interdependencies in the design space might imply that increasing the fitness of one dimension affects the fitness of other dimensions in turn. In the formal model, the attractiveness of a certain suggestion is captured by looking at the distance between the fitness of a dimension after adopting the suggested allele and the dimension's fitness corresponding with the allele that is currently chosen ($w_{n,q} - w_{n,q(now)}$).

The two forms of user feedback that determine $X_{n,q}(\beta)$ can be summarized as follows:

- Low level of user feedback: $\beta = 1 - w_{n,q(now)}$
- High level of user feedback: $\beta = w_{n,q} - w_{n,q(now)}$

Also the firms themselves can follow two strategies, expressed by exponent α. When a firm has a moderate sensing capability for monitoring user suggestions, the chance that a mutation gets selected is proportional to the attractiveness of encountered user inputs. Being the main characteristic of function 1, this occurs when α simply equals one ($\alpha = 1$). Firms with a more advanced sensing user needs capability not only monitor user feedback, but also analyse and evaluate this type of input. These firms are focused on identifying the most promising user insight that was yielded when delivering a service of a particular configuration. Here, the chance that a certain mutation will get selected is then no longer proportional to the times it is expressed: firms engaging in thorough user-centric search will be able to determine which feedback is provided most and prefer this option absolutely above other possibilities. This selective behaviour occurs when α takes very large values ($\alpha \rightarrow \infty$).

In summary:

- Inspirational sensing: $\alpha = 1$
- Exhaustive sensing: $\alpha \rightarrow \infty$

In Figure 2, below, we present the specification of the search strategies that correspond with the interaction modes. Together, the search strategies cover two main variants of searching through a design space.[1] In strategy 1 and 3, where users express a low degree of feedback, firms follow a strategy known as 'extremal search': they try to improve the weakest aspect of their product. Strategy 2 and 4 are forms of 'greedy search', which occurs when firms have more detailed information for selecting modifications with the highest fitness increase (on the level of a dimension, not the overall fitness). The difference between 1 and 3, and also between 2 and 4, is that firms with exhaustive user-search immediately select the most mentioned suggestion rather than that $P_{n,q}$ is still probabilistic by being proportional to the attractiveness of mutation n,q.

[1] We omitted random search, which would occur when firms are unable to store any information ($\alpha = 0$).

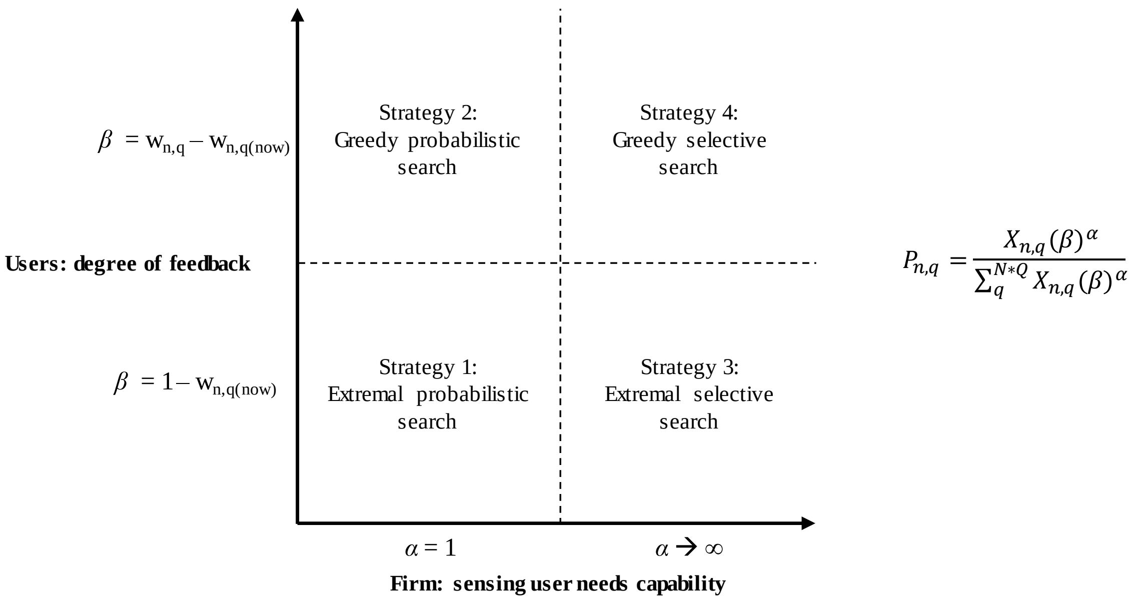


Figure 2: Operationalization of search strategies for each interaction mode

3.4. Simulation procedure

In order to run the simulation models, we first define an appropriate design space on the basis of the multidimensional framework by Den Hertog et al. (2010). According to our earlier assumptions, the level of interdependencies can be calibrated at an intermediate level (when N = 6, K = 2 or 3). Within this landscape, each dimension n can take states q = 1 ... Q. Those alleles have their own individual fitness values ($w_{n,q}$). Because of interdependencies, changing one allele might affect the fitness of other alleles. To give an example: in the simplified four-dimensional design space partially presented below in Table 1 and 2, the fitness values of dimension one (n1) and four (n4) are interrelated.[2] Each string of elements (s) in the final matrices has an average fitness W.

Table 1: Example of possible design configurations in a four-dimensional design space with 3 alleles per dimension (states of alleles expressed by A, B and C)

	n1	n2	n3	n4
s_1	A	A	A	A
s_2	B	A	A	A
s_3	C	A	A	A
s_4	A	B	A	A
s_5	A	C	A	A
s_q				
s_{81}	C	C	C	C

[2] A 4-dimensional landscape with 3 alleles/dimension, contains 81 (3^4) design configurations. Only the first 5 are shown.

Table 2: Fitness-values ($w_{n,q}$) corresponding with the design space presented above (n1 and n4 being interdependent)

n1	n2	n3	n4	W
0.1	0.2	0.6	0.1	0.250
0.5	0.2	0.6	0.2	0.375
0.4	0.2	0.6	0.6	0.450
0.1	0.5	0.6	0.1	0.325
0.1	0.9	0.6	0.1	0.425
0.2	0.7	0.3	0.5	0.425

Having defined the key parameters of our design space, we create a fitness landscape by assigning random fitness values between 0 and 1. For the example of K = 2, implying that three dimensions are mutually interrelated, the fitness value for each position q at dimension n varies for different alleles in the other related dimensions (written as $w_{n,q,q2,q3}$, in which q2 and q3 are the alleles in the other two dimensions). For the unrelated dimensions, on the other hand, the fitness values for a certain position are stable with respect to the conditions in any other dimension. In order to allow for search journeys to unfold in our six-dimensional design space, we set the number of alleles per dimension (q) at 15. Results are robust for variation in this parameter (e.g. q = 10, q = 20).

Once a design space is created, we run a simulation for all four search strategies. The specification of α and β determines the chance that a firm chooses a certain mutation. Using the chances $P_{n,q}$ for making a draw from a uniform distribution then leads to the actual selection of a mutation (see Appendix F). Each simulation consists of R number of steps. Finally, being a Monte Carlo experiment, we repeat the entire procedure MC=50 times.

3.5. Simulation results and hypothesis formulation

Inspection of the simulation results shows that most important patterns become clear within R=25. As shown in the graphs in Figure 3, these patterns are generally robust to variation in parameter K. Only if the degree of interdependencies is zero (upper left graph), strategy 4 is obviously superior. In the more realistic situation where at least a couple of dimensions are interrelated, a different order emerges.

A notable finding is that agents following strategy 1 have the lowest take-off in their fitness increase, followed by strategy 3. Both of these strategies involve a minor amount of user feedback; the difference is that agents with strategy 3 have a sensing capability for identifying what dimension should definitely be modified. The observation that agents with a modest sensing user needs capability catch up with (and eventually even take over) agents with a stronger sensing capability is even stronger if we look at the difference between firms who are frequently facing user requests (i.e. strategy 2 versus 4). Agents facing feedback on what mutations to make are generally very well able to improve the fitness of their products, but the value of sensing is now of even shorter duration. Despite initially having a high fitness-quotient (i.e. fitness increase per step), all graphs with K>0 show that the maximum achieved fitness level for strategy 4 stabilizes after a few mutations.

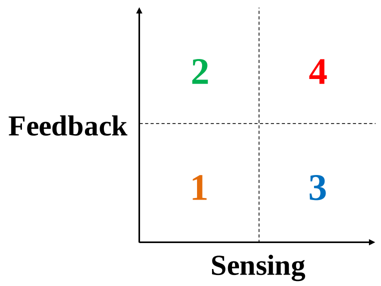
Apparently, when agents are exposed to detailed feedback (including information on unmet needs and the perceived quality of a firm's solution) and also have a strong ability to analyse user needs thoroughly, they have a risk of ending up in a local optimum. This finding is largely due to the fact that such agents respond to urgent user needs with respect to certain dimensions. Although this initially leads to rapid fitness increases, agents quickly arrive at a point where the identified position in the landscape can no longer be improved by selectively reacting to needs regarding specific dimensions. Agents who do not rely heavily on sensing, like those following strategy 2, turn out to have a higher probability of experimenting with mutations that leave more room for tweaking and tuning. The same holds for agents who do develop (and use) a strong sensing capability, but are exposed to users who do not articulate their requests explicitly.

For the case of firms providing customized services, our simulations would suggest that user feedback generally has a positive effect on innovation success: agents with a high degree of user feedback initially outperform those with a lower level. To a lesser extent, the capability of sensing user needs is likely to be beneficial for innovation efforts as well. By having a substantially strong sensing capability, firms can make use of the demands they encounter when providing their services, and thereby outperform the ones who do not invest in such ability. The comparative advantage that can be derived from this capability is thought to be more limited, compared to the benefits of facing a high degree of user feedback, because firms are tempted to focus excessively on the needs their current users are experiencing. Fulfilling those needs improves the existing product for the existing market, but might often not be the optimal choice for introducing solutions that can deliver even more value than those based on 'fixing' complaints. While agents with strategy 3 keep achieving higher fitness levels over time, this does not hold for agents who follow strategy 4.[3] Agents in the latter situation tend to reach a local optimum that is at maximum equal to the fitness levels other agents arrive at, or even lower if we look at more realistic values of K. Therefore, we would expect that the combination of having a strong sensing user capability and also facing extensive user feedback has an adverse effect on the innovation performance of customizing service providers.

On the basis of these simulation results, we arrive at the following hypothesis:

*Hypothesis: Customizing service providers' sensing user needs cap*ability and (especially) the user requests they encounter are individually positively related to innovation success, but the interaction term has a negative direction.

[3] Another reason to believe that sensing user needs might still be valuable for firms delivering customized services is that all simulated strategies are better than a random strategy in which firms have no ability to evaluate user feedback at all ($\alpha = 0$).



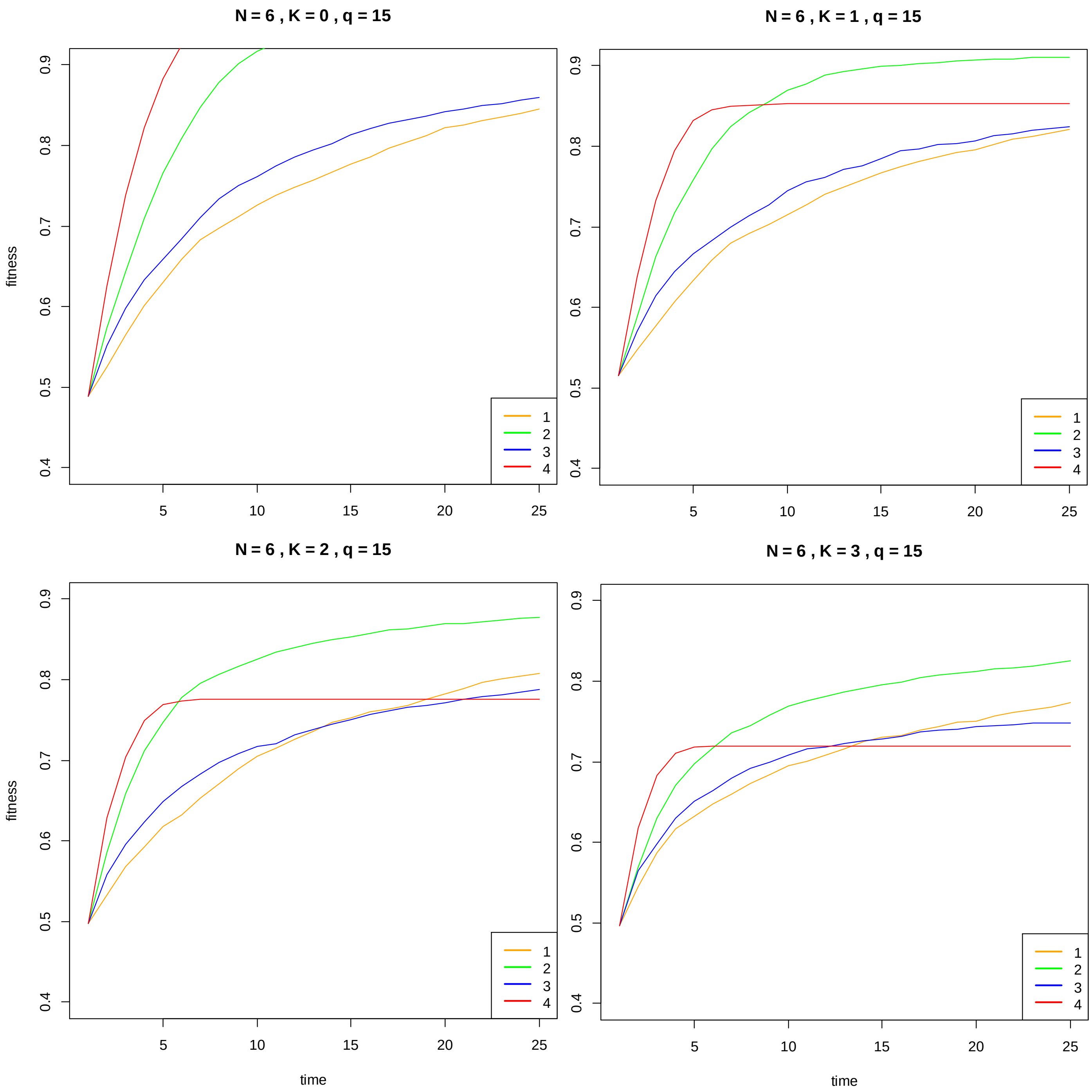


Figure 3: Maximum achieved fitness levels for K=0, 1, 2 and 3. MC = 50.

4. Empirical examination

4.1. Methodology

Sample

We examine the hypothesis with a dataset based on a survey deployed in 2011. The questionnaire was sent to single-business firms or business units with more than 10 full-time employees. Using databases from Bureau van Dijk, we retrieved contact information of Dutch firms located in the Northern Randstad. Availability of demographic information about the entire population allowed us to stratify in terms of sector and firm size; we created a multi-industry sample representative for the industry composition in the Northern Randstad.

The questionnaire was sent, in two consecutive waves, to 8054 firms. We addressed the questionnaire and accompanying letter to the CEOs or senior executives, in order to ensure that the respondents were knowledgeable about the key firm processes under investigation in this study. The questionnaire was administered by mail with the option to be filled in via the web if preferred. We obtained responses from 458 unique firms, which amounts to a response rate of 5.69%. As the survey was of considerable length, and the sample did not have any particular relation with the researchers nor the research project, the response rate was regarded as sufficient and common for similar types of research. Phone calls following up on our survey distribution learned that a large share of the addresses were outdated; out of 100 non-respondents contacted by phone, about 50 were either no longer active in the same function or no longer contactable at the address the survey was directed to. Our comparison of the demographic characteristics of respondents with those of non-respondents only showed modest differences between the two groups. This suggests that the final response was largely representative for the population we sampled.

In general, most items make use of a 7-point Likert scale ranging from “strongly disagree” to “strongly agree”. Our sample includes Dutch firms with at least 10 employees. Given the scope of our study, we only look at firms who are somehow involved in service provision. An indication for this is given by asking respondents whether they have substantial turnover stemming from services; those who did not have any revenues like that (scoring below the middle of the Likert-scale) are omitted from the current analysis (18%). The final subsample contains 292 complete cases, most of them stating to serve a relatively high number of customers via labour intensive processes in pre-dominantly a business-to-customer setting.

As noted throughout this paper, our expectations concern in particularly innovation efforts by firms who adapt their services to the needs of individual clients. It is pre-eminently in this type of service providers where interaction is high, and where firms can experiment with the user feedback they receive. Figure 4 shows the distribution of responses to the question whether firms in our sample tailor their services. Most of our respondents appear to be heavily engaged in customization, which is hardly surprising if one realizes that meeting individual requests of clients is often seen as an inherent part of service provision: "Services are intangible activities customized to the individual request of known clients" (Pine and Gilmore, 1999, p.8). Nevertheless, some firms indicate to tailor their services only to a limited extent. Since we wish to focus on customizing service providers, we perform our analysis primarily on firms who responded with a 6 or 7 on the Likert-scale. The remaining 218 cases account for 75% of our final sample.

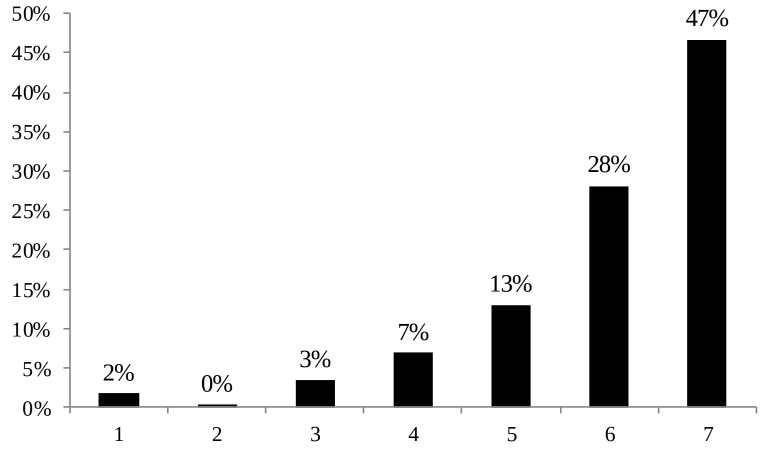


Figure 4: Distribution of answers on the statement: "Our services are customized", on a 7-point Likert scale.

Variables and statistical models

Our main question is which interaction mode is most conducive to successful innovation. Accordingly, the dependent variable is constructed with survey-items asking how much of a firm's turnover stems from improved or newly introduced products. Following the CIS-guidelines (OECD, 2005b), these products can be services, goods, or combinations thereof. What matters in this study is that a firm is at least engaged is some extent of service provision, and thus direct customer interaction: the exact form of the innovation that is ultimately being realized is considered to be irrelevant. Given the truncated distribution of turnover figures (see Figure 5), ranging between 0% and 100%, relations between our variables are assessed with multivariate Tobit regression models (Laursen, 2011).

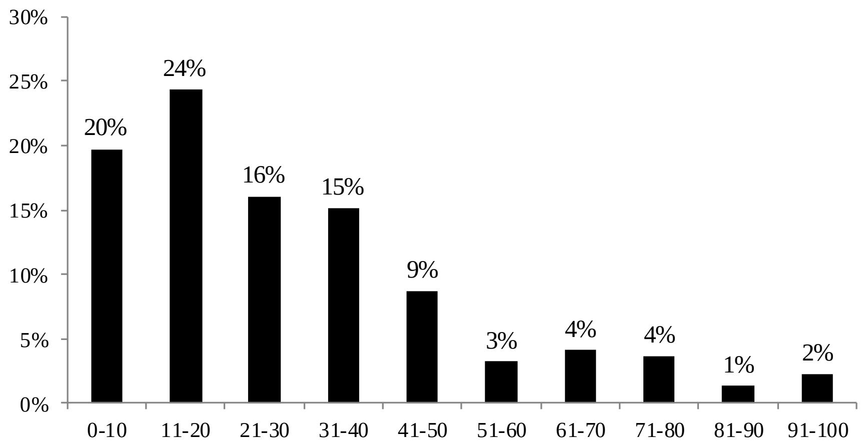


Figure 5: Distribution of dependent variable for sample of customized service providers (n=218).

As for the independent variables: the multi-item measurement scale for sensing user needs capability (based on Den Hertog et al., 2010) has been constructed and applied by Janssen et al. (2014). Again, we take the average of the underlying three items as a measure for the strength of this capability. The item for User Requests ("Our clients regularly ask for new goods and services") stems from work by Jansen et al. (2006). Both independent variables resemble a normal distribution. When firms are exposed to a low level of user requests, they only can base their entrepreneurial experimentation on the complaints they receive during regular service delivery. In case users often ask explicitly for new solutions, they provide more detailed information on what aspects of a service to modify (search strategy 2 and 4). Using hierarchical modelling, we first include both independent variables in our regression model before extending it with an interaction term. Such an analysis sheds light on the combined effect of sensing user needs and user requests along all values that both variables can take. In this analysis, however, we are especially interested in the question whether sensing user needs can have an adverse effect when firms are exposed to high degrees of user requests. Following Spiller et al. (2013), we therefore also conduct a so-called floodlight analysis to examine at which particular values for user requests a possible interaction effect occurs.

Finally, to control for the fact that user requests and innovation might be more common in turbulent markets, a variable for market dynamism is included in the model (retrieved from Jansen et al., 2006). The logarithm of firm-size is used as a control variable as well, just like a construct that indicates to what extent a firm has formalized R&D efforts.

Table 3, below, shows the descriptive statistics of the variables in our models. These models generally have the following form (see Table 3 for variable codes):

$$Y = \beta_0 + \beta_1{*}C1 + \beta_2{*}C2 + \beta_3{*}C3 + \beta_4{*}X1 + \beta_5{*}X2 + (\beta_6{*}X1{*}X2) + \varepsilon$$

Table 3: Descriptive statistics and correlations (in italics) for sample of customized service providers (n=218)

Customized services (n=218)	Mean	Std. Dev.	C1	C2	C3	X1	X2	Y
C1. Firm size (log fte)	3.42	1.156						
C2. Formalization	3.47	1.331	.037					
C3. Market dynamism	5.45	1.391	-.011	.140*				
X1. Sensing User Needs (S.U.N.)	4.70	1.173	.097	.363**	.221**			
X2. User Requests (U.R.)	4.44	1.626	-.046	.325**	.572**	.312**		
Y. Turnover from new or improved offerings (%)	32.90	22.515	-.086	.020	.137*	.164*	.290**	

4.2. Regression results

Table 4 presents the regression results. Although market dynamism is strongly related to user requests, the control variable is not significantly related to turnover from innovation. The contrary holds for formalization of innovation efforts. Its negative direction is consistent with the general finding that service firms can (and often do) innovate without engaging in formal R&D (Miles, 2007). In fact, our overall regression results emphasize that looking at structured but not necessarily formalized activities, like dynamic capabilities, is a suitable option for analysing how service providers achieve innovation success.

The findings from our empirical analysis turn out to be largely in line with the hypothesis derived from simulating the different user-producer interaction modes. For firms that provide customized services, sensing user needs has a weak but positive effect on the appropriated turnover from innovation. In accordance with the simulation results, user requests appear to be relatively more important, as indicated by a bigger beta coefficient and significance value (Model 1). The interaction term of both factors, shown in Model 2, is weakly significant and has a negative direction.

The encountered interaction effect is obtained when both continuous independent variables are multiplied. Since the mechanism we hypothesized concerns the diminishing effect of sensing user needs (S.U.N.) at in particular high values of user requests (U.R.), we continue by decomposing the interaction (Spiller et al., 2013). To do so, we dichotomize the user requests variable at all possible thresholds. Creating these dummies allows us to run a series of 'spotlight regressions' in which we test the interaction of S.U.N. and U.R. at the full range of U.R.'s cut-off values.[4] Jointly, the spotlight regressions make up a floodlight analysis revealing the Johnson-Neyman point: the value where the interaction term starts to be significant (Spiller et al., 2013). In our sample, the switching point appears when U.R. exceeds a value of 5. This value, marking the median of the response to this question, is just above the middle of the Likert-Scale. Models based on cut-off values below U.R. = 5 do not yield a significant interaction (only the direct effects of S.U.N. and U.R. are significant and positive), while the two models above this point confirm that sensing user needs combined with ample user requests has a significant and negative relation with innovation-based turnover (see Model 3 for U.R. threshold = 5; the model with threshold at 6 has an interaction term with significance at the level of p < .001).

Table 4: Regression results for sample of customized service providers (n=218)

Y = % turnover from improved / new offerings	Model 1 Beta	(Std. error)	Model 2 Beta	(Std. error)	Model 3 Beta	(Std. error)
Intercept	19.153**	(8.516)	-8.825	(17.267)	22.608**	(9.371)
Firm size (log fte)	-1.567	(1.255)	-1.827	(1.253)	-2.252*	(1.234)
Formalization	-2.023*	(1.199)	-2.018*	(1.190)	-1.975*	(1.166)
Market dynamism	-0.938	(1.267)	-0.757	(1.261)	-0.423	(1.163)
Sensing User Needs (cont.)	2.580*	(1.360)	8.539**	(3.530)	4.958***	(1.538)
User Requests (cont.)	4.410***	(1.146)	10.903***	(3.676)		
S.U.N.*U.R.			-1.373*	(0.739)		
User Requests (binary)[a]					52.563***	(14.516)
S.U.N.*U.R. (binary)[a]					-7.507***	(2.807)
Wald-statistic	27.03		30.91		36.34	
df	5		6		6	
p	0.000***		0.000*		0.000*	

* = p <.10, ** = p < .05, *** = p < .01

[a] = Dummy for user request, threshold is ≤5 (U.R. = 0) versus >5 (U.R. = 1). See description of floodlight analysis.

[4] Because user requests are measured on a 7-point Likert scale, we can make six separate dummies (Dummy 1: U.R. = 1 versus U.R. = 2-7; Dummy 2 = U.R. = 1-2 versus U.R. = 3-7; etc.).

The results of Model 3 are also visualized in Figure 6, clearly showing that firms facing only a low amount of user requests do benefit from having a strong sensing capability. The contrary holds for firms more often exposed to user requests: generally their innovation-based turnover is relatively high, but this decreases as firms start to rely more on their sensing capability.

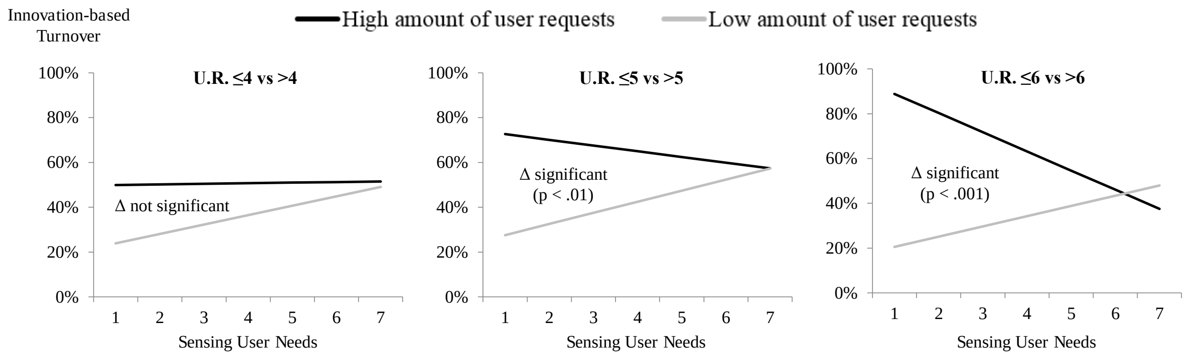


Figure 6: Visualization of regression parameters for models based on different thresholds for user requests (U.R.).
The moderating effect of U.R. (i.e. difference between the slopes) only is significant when the threshold lies at U.R. ≥ 5.

4.3. Extension: non-customizing service providers

In order to strengthen our evidence, and to reduce the possibility of explaining our results with alternative mechanisms, we extend our investigation by looking at the earlier excluded group of non-customizing service provides. The delivery of non-tailored or standardized services typically requires less co-production and thus user-producer interaction, which is why providers of such services form an excellent comparison group within the domain of services (Tether et al., 2001). On this basis, we repeat the regression analyses for the sample of non-customizing service providers (n=74). As for the descriptive statistics of this comparison case; none of the differences with the focal group (with respect to variable means) is statistically significant. Thus, at the outset, both groups are on average equally innovative, encounter a similar degree of user feedback, and have similar capability strengths.

Models 4 and 5, shown in Table 5, cover the comparison situation in which service providers do not customize their solutions. For them, sensing user needs appears to be of significant value, as opposed to user requests. Note, however, that the overall model is only weakly significant. If we include the interaction term for sensing user needs and receiving user requests (continuous variables), the overall model fit improves to $p < .05$, and we notice that both independent variables significantly reinforce each other. A floodlight analysis reveals that this positive interaction already starts to be significant at the cut-off of U.R. = 4 ($p < .05$), but for comparison reasons we show again the results for the variable based on a threshold of 5 (see Model 6). The positive direction of the interaction term is contrary to the observations retrieved in the group of firms providing customized services, which implies that for innovation in more standardized services the myopia risk might be less likely to occur.

Table 5: Regression results for comparison case of non-customized service providers (n=74)

Y = % turnover from improved / new offerings	Model 4 Beta	(Std. error)	Model 5 Beta	(Std. error)	Model 6 Beta	(Std. error)
Intercept	3.886	(14.679)	64.282	(32.401)	27.882*	(16.545)
Firm size (log fte)	0.768	(1.657)	0.662	(1.611)	0.724	(1.569)
Formalization	-4.403**	(2.220)	-4.439	(2.158)	-3.421	(2.147)
Market dynamism	0.822	(2.010)	-0.511	(1.960)	0.416	(1.754)
Sensing User Needs (cont.)	5.650**	(2.454)	-7.880	(6.939)	1.339	(2.940)
User Requests (cont.)	2.009	(1.910)	-9.856	(6.009)		
S.U.N.*U.R.			2.726**	(1.313)		
User Requests (binary)[a]					-29.894	(19.715)
S.U.N.*U.R. (binary)[a]					8.592**	(4.028)
Wald-statistic	10.13		15.03		18.13	
df	5		6		6	
p	0.072*		0.020**		0.006***	

* = p <.10, ** = p < .05, *** = p < .01

[a] = Dummy for user request, threshold is ≤5 (U.R. = 0) versus >5 (U.R. = 1). See description of floodlight analysis.

5. Discussion

Aimed at contributing to scholarly debates on user-producer interaction in innovation processes (Rosenberg, 1969; Lundvall, 1988; Chatterji and Fabrizio, 2012), the current paper provides a theoretical argument for why investing heavily in a sensing capability might have adverse effects for customizing firms exposed to a high amount of user requests. So far, little profound effort has been made to understand how exactly the use of user knowledge affects the success of search processes (Chatterji and Fabrizio, 2014; Laursen, 2011). Our answer to this gap has the form of simulations based on a formal representation of various forms of user-producer interaction. By describing the respective merits and pitfalls of four concrete search strategies, the theoretically grounded NK-model and the empirical examination thereof add to a discourse that is being dominated by intuitions and contradicting results.

The mechanisms described by our simulations are consistent with the pitfall warned for by Christensen in his influential work on the innovators dilemma (1997). His ideas on the caveat of being misled by market demand have originally been developed in the context of established firms tempted to focus on their existing customers, thereby overlooking possibilities to serve a potentially more profitable user base. Here, rather than focusing on how incumbents and entrants explore new markets, we have shown how the myopia principle also applies to customizing service providers who are heavily exposed to user requests. The proposed NK-model describes how they face a challenge which is rather similar to the innovators' dilemma, except that it concerns the tension between focusing on individual needs versus exploring solutions to broader needs (yet possibly still in the same client base).

The simulation results demonstrated that listening carefully to demanding customers is particularly useful for identifying the most efficient and immediate improvements, but when relying heavily on sensing abundant user feedback, agents in our model run the risk of getting stuck in a suboptimal configuration. Accordingly, also our empirical examination suggests that firms who tailor their services to demanding users might be tempted to focus strongly on encountered needs, and therefore go down an unfruitful path of 'local optimization'. Such excessive attention to their clients can prevent them from seeing possibilities for introducing genuinely new improvements or commercializing solutions in other contexts. Thus, in order to keep improving, it appears wise to also engage in experiments that are not exclusively based on the user's own (more or less detailed) ideas of what would be a viable adaptation of the current offering. Pointing at the importance of overcoming local search (Rosenkopf and Almeida, 2003), this mechanism explains findings like the ones presented by, for instance, Laursen (2011) who observes that innovation performance is negatively affected when firms do not complement intensive user-producer interaction with sourcing other knowledge channels. Similarly, it is consistent with earlier findings that service providers benefit more from investing in other aspects of knowledge generation and application than concentrating their efforts on intensifying user-producer interaction (Mina et al., 2014).

By building on recent attempts to conceptualize service innovation as the search in multidimensional design space, this study also forms a contribution to the currently unfolding debate regarding NK-modelling in the context of services (Chae, 2012a, 2012b; Desmarchelier et al., 2013). Moreover, from a methodological perspective, we aim to advance innovation studies by showing how a simulation study can be complemented with an empirical validation. To our knowledge, such a combined approach is of considerable originality to the audience we address. Possibly it can inspire more research on understanding and afterwards validating mechanisms of which the interaction is unknown at the outset.

6. Conclusions

With this study we have sought to explain the paradox that those firms who are most engaged in fulfilling actual user needs might be the ones who benefit less from developing a capability for sensing user needs. Strategic considerations regarding the use of user knowledge differ across various lines of literature. On the one hand, studies focused on manufacturing industries tend to argue that innovation processes often benefit substantially from investing in activities for sensing user needs. Service-oriented research, on the other hand, commonly stresses that the relational nature of efforts to meet individual customer needs provides opportunities for firms to acquire user feedback already during regular business activities. Only few existing studies asked whether a strong capability for sensing user needs is essential for service firms to develop new ways for meeting customer demand. We examined to what extent the benefits of openness to user insights depend on the behaviour of a service firm's clients, and in particular whether explicit requests for new solutions or experiences can make a sensing capability a weakness rather than a strength. For firms who tailor their services to the user requests they are receiving, a myopic focus on introducing quick-win incremental changes might be a serious caveat.

Since customer interaction is an inherent characteristic of service provision, this study is predominantly focused on firms that co-produce intangible solutions together with their clients. However, we have no reasons to believe that our results are exclusive for service providers only: this study might also inform specialized suppliers who resemble the manufacturing equivalent of customizing service firms (Cusumano et al., 2014). Likewise, we already noted that also manufacturing firms are increasingly adopting or even switching entirely to service-based business models. The finding that sensing is of limited relevance under certain circumstances might therefore also be of relevance to industries where ‘opening up’ is still actively proclaimed (Chesbrough, 2011). By looking at service-characteristics that are becoming prevalent for an increasing number of firms, we contribute to on-going efforts of exploring how peculiarities of service innovation hold implications for our general understanding of novelty creation in modern economies (Drejer, 2004; Miles, 2007). This study can be regarded as another advance in the line of research that aims to make innovation theories, in particular with respect to openness, more sensitive to the peculiarities of service provision (Mina et al., 2014).

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Appendix 1: Clarification on simulation procedure

This appendix clarifies according to which mechanisms agents in our simulation choose a particular mutation. In the partially depicted landscape from Tables 1 and 2, an agent can start at position (n1,q1; n2,q1; n3,q2; n4,q1), which is string s_1 in the upper row.

If the user feedback has type $\beta = 1$, an agent will observe the following 'attractiveness-values' (Table F.1 is based on $X_{n,q} = 1 - w_{n(now)}$; values for $w_{n(now)}$ are underlined). Search strategy type 1 implies that an agent only uses feedback for determining which dimension to change, which is why parameter q can actually be removed here. Which specific allele is chosen on that dimension results from random selection.

Table A1.*1. Information available to agents with β = 1. (X_n =* attractiveness of changing dimension n**)**

	n1	**n2**	**n3**	**n4**
X_n	1 - $\underline{0.1}$ = 0.9	1 - $\underline{0.2}$ = 0.8	1 - $\underline{0.6}$ = 0.4	1 - $\underline{0.1}$ = 0.9

If we ignore α (i.e. $\alpha = 1$, like in strategies 3 and 4), the possibilities for selecting a certain mutation are linearly proportional to the relative attractiveness of mutations. Note that we only look at the chance that a dimension gets changed: which allele is chosen for the mutation is just a random choice. We can state that all alleles q for a certain dimension have equal chance of being selected, so again, index q in formula below can be left out.

$P_{n1.q} = 0.9 / (0.9+0.8+0.4+0.9) = 0.30$
$P_{n2.q} = 0.8 / (0.9+0.8+0.4+0.9) = 0.27$
$P_{n3.q} = 0.4 / (0.9+0.8+0.4+0.9) = 0.13$
$P_{n4.q} = 0.9 / (0.9+0.8+0.4+0.9) = 0.30$
$\sum P_{0\text{-}n.q} = 1$

If the user feedback has type $\beta = 2$, the selection procedure is more advanced. The attractiveness now depends on the fitness increase that occurs at a certain dimension when adopting a particular suggested allele. We take a piece of the earlier shown fitness landscape to illustrate the effect of interdependencies in the design space (for original fitness values, below underlined, see Table 2). The first three strings relate to changing n1 while keeping n2 constant, whereas string 4 and 5 relate to changing n2 while not changing alleles of dimension n1. In the four possible mutations below, s_5 would denote the biggest fitness increase (+0.7 at dimension n2). However, as we can see in Table F.2, s_3 would yield better overall results (total fitness W) due to the interdependency with n4.

Table A1.*2: Information available to agents with $\beta = 2$. ($X_{n,q}$ =* attractiveness of changing to allele q on dimension n)

String	**notation of configuration**	$\mathbf{X_{n,q}}$
s_1	A,A	(current)
s_2	B,A	0.5 - <u>0.1</u> = 0.4
s_3	C,A	0.4 - <u>0.1</u> = 0.3
s_4	A,B	0.5 - <u>0.2</u> = 0.3
s_5	A,C	0.9 - <u>0.2</u> = 0.7

Again, we can now calculate the probability that a certain mutation gets selected. Let's pretend that the five strings above are all available options, so there are four alternatives to current position s_1 (A,A).

$P_{n1,B} = P_{s2} = 0.4 / (0.4+0.3+0.3+0.7) = 0.24$

$P_{n1,C} = P_{s3} = 0.3 / (0.4+0.3+0.3+0.7) = 0.18$

$P_{n2,B} = P_{s4} = 0.3 / (0.4+0.3+0.3+0.7) = 0.18$

$P_{n2,C} = P_{s5} = 0.7 / (0.4+0.3+0.3+0.7) = 0.41$

$\sum P_{0\text{-}n,q} = 1$

Appendix 2: Items for measuring 'sensing user needs capability'

Items based on from Den Hertog et al. (2010). See measurement scale development by Janssen et al. (2014).

- We systematically observe and evaluate the needs of our customers.
- We analyze the actual use of our services.
- Our organization is strong in distinguishing different groups of users and market segments.