The perils of pleasing: Innovation-stifling effects of customized service provision

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Abstract

Sensing customer needs capabilities generally help firms to utilize customer feedback. Yet, as research linking micro-economics to industrial dynamics has shown, a strong focus on such feedback may prevent an adequate response to more promising market developments. We analyse this tension for firms providing customized services, whose innovativeness heavily depends on customer input. By drawing upon an NK search model, we simulate various interactive search strategies. Our simulations result in hypotheses concerning the strategies' relation to innovation-based turnover. We use survey data from 292 firms to substantiate our expectations empirically. Both our simulation and regression results point to a positive influence on turnover of sensing customer needs and of customer feedback. While the interaction effect is positive for non-customizing service providers, it is negative for their customizing counterparts. The latter group may fail to exploit their inventiveness, as they concentrate on tuning new services to the specific needs of existing customers rather than turning them into more widely marketable innovations.

Keywords Customer feedback · Customization · Capabilities · Evolutionary search · NK · Simulation

JEL Classification O32 · D83 · L80 · O31

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1 Introduction

It is increasingly understood that service encounters might provide a fruitful basis for innovation (Leiponen 2005; Lages and Piercy 2012; Sundbo et al. 2015). Delivering services is essentially a process in which firms like engineering companies, consultancies, design bureaus or 'servitized' manufacturers co-produce value together with their customers (Tether et al. 2001; Bowen and Ford 2002; Gallouj and Windrum 2009). The associated customer-seller interaction can yield insights that are informative for improving service providers' existing products as well as for developing new ones (Lundvall 1988; Chatterji and Fabrizio 2012, 2014). As a result, firms are encouraged to invest in capabilities for sensing customer needs as a means to evaluate, process, and integrate feedback effectively (Teece 2007; Den Hertog et al. 2010). Such capabilities are embedded in organisational routines for processing information on customer demands. Strong capabilities involve systematically analysing and interpreting signals, while weak capabilities are typically geared to collecting simple feedback only (Day 2002; Teece 2007). Generally, well-developed sensing capabilities are believed to be crucial if a firm is to stay adaptive and competitive (Bharadwaj and Dong 2013).

A strong customer-centred approach to pursuing innovation, however, does not guarantee successful outcomes (Felin et al. 2017). Hamel and Prahalad (1991) and Christensen and Bower (1996) have suggested that a strategy focused on optimally fulfilling the demands of existing customers can lead firms to ignore other potential customers. Over the past decades, the caveat known as 'the innovator's dilemma' (Christensen 1997) has been echoed in a myriad of studies on technology strategy, organizational change and disruptive innovation (e.g. Danneels 2002; Danneels 2003; O'Reilly and Tushman 2008; Laursen 2012). As existing customers exert greater influence than potential customers, firms are held captive by their current customer base, searching only for new solutions along established paths (Laursen 2011). Investing in sensing customer needs may, therefore, tie down the firm's resources to myopic innovation, which neglects the development of new customer segments.

To what extent the sketched peril also holds for service firms providing customer-specific and largely intangible solutions is far from obvious. According to recent research, it is recommended to asses this by also considering the customization degree of service offerings (Cabigiosu and Campagnolo 2019). Depending on whether provided services are tailored or standardized, firms are required to engage more or less intensively with individual customers (Tether et al. 2001; Laursen 2012). The customers' actions and signals provide cues to which firms may respond when pursuing improved customer satisfaction. This customer feedback can vary in its intensity and clarity: in some cases, customers are simply sending complaints while, in other cases, they are more willing and able to offer suggestions for service improvement (Alam 2002; Baldwin and von Hippel 2011). A high dependence on interaction with customers that continuously provide signals can, in turn, be fed into the process of new product development (Tether et al. 2001; Visnjic Kastalli and Van Looy 2013). The outcomes of customer

sensing capabilities are thus driven by recursive mechanisms affected by both firm and customer characteristics: the customization levels of a firm's offerings and the quality of feedback provided by its customers (Gallouj and Weinstein 1997). Linking back to the innovator's dilemma, we pose the question whether these characteristics also influence the risk of using sensing capabilities for moving towards services tuned solely to existing or small sets of customers.

As existing research has barely touched upon the influence of customization on feedback utilization amongst innovation pursuing service providers, there is an insufficient basis for theorizing on performance implications. In this paper, we use simulations to explore the relationship between sensing customer needs capabilities, feedback quality and the degree of customization, on the one hand, and innovation-based firm performance, on the other. We draw upon the literature on evolutionary search processes and the NK model (Kauffman 1993; Levinthal 1997) to identify four basic types of interactive search strategy used to experiment with new service offerings in a multidimensional design space (Chae 2012a; Querbes and Frenken 2017; Vuculescu 2017). The model and corresponding performance pay-off simulations allow us to make sense of the complex interrelatedness among our key concepts, and to formulate hypotheses. The interaction between customer feedback quality and sensing customer needs capabilities is expected to have a positive influence on a firm's innovation success when its offerings are standardized. The interaction is predicted to have a negative effect when firms offer customized services.

In a second stage, we use field data from a firm-level survey of 292 Dutch firms to test the extent to which sensing capabilities and customer feedback are related to innovation-based turnover. The regression results support the findings from the stylized simulation model. Contrary to their less-customizing or non-customizing counterparts, customizing service providers can fail to increase innovation-based output when focusing strongly on articulated customer needs. While a relentless commitment to fulfilling customer needs may offer short-run benefits, untempered tailoring can act as a distraction. Rather than choosing a suboptimal product standard (typical for myopic innovation in goods-centred firms), it may well be the customer-specific fine-tuning of solutions that prevents customizing firms from deploying innovation with a large market potential. These findings shed new light on what might cause firms to rely excessively on customer feedback, which is usually believed to be a matter of the firm's and customer behaviour only. The fact that no drawback is observed for firms hardly customizing their services suggests that also the provided type of offering is crucial in this respect.

This study contributes to the (service) innovation strategy and management studies literature by elaborating specific conditions that can explain the outcomes from investing in customer-sensing capabilities. The rare combination of simulations and initial empirical tests has allowed us to highlight certain boundary conditions that nurture myopic innovation (Ganco 2017; Dosi et al. 2019; Baumann et al. 2019). A second contribution is specific to the literature on the innovation of customized services (Visnjic Kastalli and Van Looy 2013; Cabigiosu and Campagnolo 2019). Firms providing such offerings arguably form the vanguard of firms whose core business consists of delivering and developing differentiated offerings tailored maximally to the needs of – and co-created by – individual customers (Tether et al.

2001; Alam 2002). In their wake, we find an increasing number of manufacturing firms realizing that globalized economies and communication technologies promote customer-centric business models rather than the traditional supply-impelled market logic (Teece 2010; Baden-Fuller and Mangematin 2013; Hienerth et al. 2011). With customizing service providers leading the way into customer-needs-driven business strategies, investigating their dependence on sensing capabilities and feedback is relevant both from a theoretical and an empirical point of view.

The remainder of the paper is as follows. In Sect. 2 we develop a theoretical framework regarding the interaction between a firm's sensing activities and its customers signalling activities. In Sect. 3 we theorize on the moderating role of customization. The design and outcomes of our simulation models are presented in Sect. 4, which results in the hypotheses that are empirically tested in Sect. 5. Section 6 concludes.

2 Framework development

2.1 The (contested) importance of customer feedback for customized services

Services emerge from a process in which a firm and its customers mobilize their competences – possibly in relation to technologies – when seeking to satisfy customer needs (Lancaster 1966; Gallouj and Weinstein 1997). The act of providing customized services, in which firms continuously receive information about customer demands, ultimately results in a unique value proposition (Vargo and Lusch 2004). For a consultancy, this could be a technical, legal or financial solution, such as a novel method of designing products, planning maintenance, running a franchise, calculating costs, or organizing human resource issues. One of the many documented examples is Deutsche Bank: its tailored derivative products, developed while visiting a particular customer, often tended to be of interest to other customers too (Ramdas et al. 2012). Similarly, looking at manufacturing industries switching to service solutions, Kowalkowski et al. (2012) recognize that new propositions typically arise from customized offerings that become encoded and formalized.

Characteristic for the *ad-hoc* inventions or enhancements coming out of interactive production processes is that they only become successful innovations once they have been commercialized in other contexts (Drejer 2004; Srinivasan et al. 2015). Replicating and scaling up co-created inventions is, therefore, a major challenge for customizing service providers with innovation ambitions (Toivonen and Tuominen 2009; Tether 2005). Considering that customer feedback is a key driver of novelty creation occurring in the first place, one might expect that sensing customer needs capabilities are crucial for customizing service providers looking to develop new and better market propositions. Then again, consistently responding to expressed needs could also be a myopia-induced dead-end street (Laursen 2011).

2.2 Customer feedback as a source of variation

Customer feedback entails the spectrum of signals that customers provide to express their (dis)satisfaction and suggestions for improvements or new functionalities. When it comes to understanding and identifying new market needs, as well as optimizing existing products, customers themselves are often better positioned than firms (Bogers et al. 2010). This holds especially for lead users, whose strong needs precede wider market demands (Von Hippel 1986). By incorporating customer-based knowledge, firms can direct their search efforts towards further elaboration and large-scale commercialization of fruitful customer ideas (Chatterji and Fabrizio 2012, 2014).

A characteristic of service providers is that they directly deliver the desired functionality or experience itself rather than a standardized artefact (Pine and Gilmore 1999). Meeting the requests of individual customers requires knowledge that can only be obtained through intensive interaction (Matthing et al. 2004). Service delivery is often understood as an interactive process in which a provider and a customer jointly aim to fulfil the customer's needs (Vargo and Lusch 2004). The extent to which they succeed is determined by how well both parties align their resources and competences in this act of co-creation (Vargo and Lusch 2008). During the simultaneous processes of (co-)production and consumption, service customers continuously give out valuable signals (Cusumano et al. 2015; 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; Alam 2002).

The *lowest degree of feedback* quality consists of satisfaction levels. Customers can implicitly or explicitly signal the extent to which they are pleased with the service being delivered and whether it meets their needs (Matthing et al. 2004). Of particular interest is how customers communicate their appreciation or frustration during the very acts of co-production and consumption (Gustafsson et al. 2012). The interactive nature of service provision allows customers to immediately send out evaluative signals to the (front-office employees of) the organization they are dealing with. Apart from being more direct, such interaction provides opportunities for customers to express in detail what specific aspect of a service satisfies or dissatisfies them. These signals, respectively, can support decisions whether to maintain or alter the properties of the provided service. In particular, complaints about a certain feature may provide incentives to search for alternative ways of delivering an offering.

Higher degrees of feedback quality also contain requests for particular improvements. By explicitly formulating a demand for new services, customers can inform a firm about the needs they would like to see fulfilled. When reviewing research on customers as a source of innovation-related knowledge, Bogers et al. (2010) state that information about unmet needs is likely to go hand in hand with suggestions on how to address them. Customers coming forward with a specific need are often found to provide cues for a possible service: "expressed needs may have either expressed or latent solutions" (Gustafsson et al. 2012, p. 313). As a result, front-end professionals not only obtain inspiring in-depth insights into a customer's use-situation but, being faced directly with customers' perceptions of problems and unmet needs, they often garner ideas on which improvements to make (Rubalcaba et al. 2012).

In the light of searching for innovative services, it should be noted that customer demands and suggestions are especially valuable since they are very often original, timely and comprehensive (Bogers et al. 2010). However, they often are also fragmentary, less producible and unelaborated (Magnusson et al. 2003). Knowledge stemming from the experience of personal use tends to be specific to individual needs – latent or articulated – and, therefore, only covers a limited part of the body of knowledge required to implement a total solution (Riggs and Von Hippel 1994; Sandulli 2013). Thus, the above-mentioned forms of feedback pertain mostly to evaluations and suggestions for particular aspects of a service: it remains up to the firm to determine how to use this knowledge to improve the entire offering (Vargo and Lusch 2008).

2.3 Organizational capabilities for sensing customer needs

Recognizing the importance of customer demands begs the question how firms can make strategic use of this information. In the context of service providers, the distance to customers is smaller than for firms that manufacture physical goods exclusively. However, given that service delivery essentially pertains to fulfilling customers' actual needs instead of providing them with an intermediary artefact, it seems all the more important to keep track of their needs. Here, we are mainly interested in the characteristic that service providers are continuously exposed to some sort of feedback but have to decide how to deal with this. Studies on customer involvement suggest that the best way to acquire customer knowledge is by interacting with them 'in situ' rather than by setting up experimental settings (Edvardsson et al. 2012). Sensing customer needs capabilities can be regarded as the organizational routines allowing a firm to obtain and process the signals retrieved from such interactions (Teece 2007).

In order to understand the needs expressed by customers, organizations deploy activities that help them to gather and evaluate the signals they encounter. According to Matthing et al. (2004), service providers can respond aptly to customer 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).

A *low sensing capability* level allows firms to obtain signals, without necessarily doing so in a systematic way (Day 2002). According to Teece (2007), sensing is one of the most crucial capabilities for firms to develop. Most service providers have, to some extent, an intelligence function for keeping track of what existing or potential customers want (Den Hertog et al. 2010). Deploying a capability for market sensing activities provides firms with a lodestar on where to concentrate efforts, as the sensed feedback can provide clues on which aspects of the offering to improve (Von Hippel 1986).

Fig. 1 Four typical modes of user-producer interaction that service providers can engage in
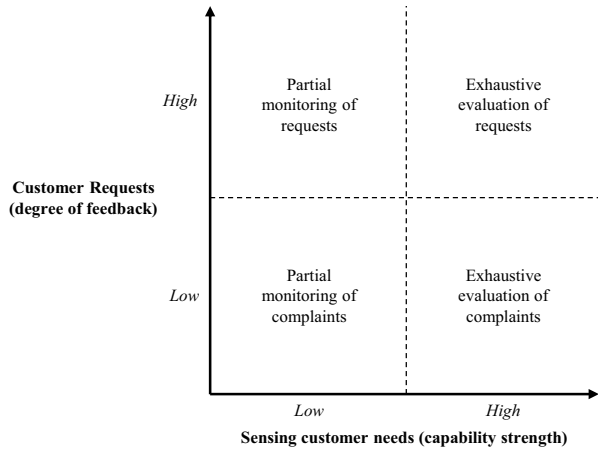
Firms having a *high sensing capability* level carefully administer and systematically evaluate feedback in order to select the most urgent modifications. When assigning a particularly high priority to customer demands, they might screen those comments that are expressed most often and most urgently. Firms deploying a wide range of advanced sensing practices arrive at a point where customers play a truly central role in the search for better propositions: customer knowledge is then 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 customers really want and to focus their resources on fulfilling truly pressing needs.

2.4 The interaction between firms and their customers

By discriminating low and high levels of both sensing activities (by firms) and feedback signalling activities (by customers), we identify four typical modes of customer-producer interaction (Fig. 1).

As for the behaviour of customers, feedback originating from direct interaction can tell a service provider, first of all, that something needs to be changed, followed by *which* particular aspect based on expressions of (dis)satisfaction and signals of unfulfilled needs. If customers provide a higher degree of feedback, their demands can give an indication of *how* this can best be done, i.e. *which* changes are thought to be most suitable. Customers who frequently express their requests provide information that is more likely to contain concrete suggestions than mere complaints.

Firms, in turn, can obtain inspiration for innovative services by monitoring how their customers use and experience provided services. Monitoring is only partial when firms lack the ability to centrally collect and analyse the signals they encounter. By investing more substantially in their sensing capability, firms can take a user-centric approach in which they follow their customers closely. This allows them to adjust and optimize services more precisely to identified needs.
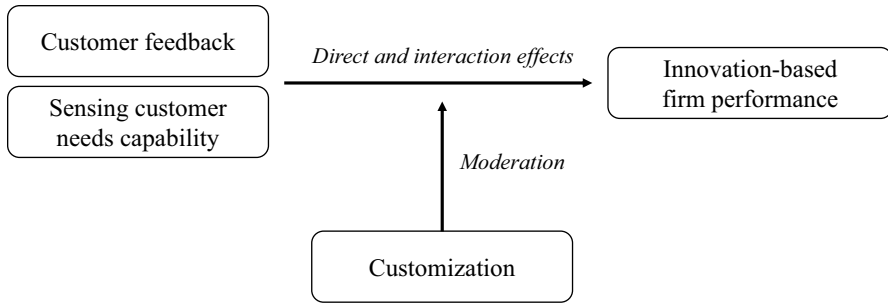
Fig. 2 Conceptual model of relations between key concepts

3 The moderating influence of customization

Deciding whether to invest resources in sensing requires insight into the respective advantages of each interaction mode, including the conditions under which these advantages are most prominent. The literature on innovation in services has paid little attention to the connection between a firm's customer environment and capabilities, on the one hand, and its innovation-based performance, on the other (Damanpour et al. 2009). In terms of contextualization, we are particularly interested in the influence of customization as a characteristic of the offering a firm is providing.

According to Pine and Gilmore (1999, p. 8), all service solutions are "intangible activities customized to the individual request of known clients". However, it is well-understood that the processes required for service production and service delivery can also be standardized to a certain extent (Wright et al. 2012). Kipping and Kirkpatrick (2013) note, for instance, that, relative to traditional management consulting firms, IT-based service firms are more inclined to rely on standardization of skills (through shared values, habits, mental frameworks) and procedures. Furthermore, some services allow for mass customization (Pine 1993); adapting standard services to customer requests for differentiation is increasingly common amongst service providers (Yoo and Park 2016). The latter typically comprises a product architecture involving standardized interfaces or 'modules' that service providers can mix and match to meet customer needs efficiently (Voss and Hsuan 2009).

When studying the potential innovation impact of (sensing) customer needs on innovation performance, the customization level of the service a firm is offering can be conceptualized as a moderating factor; see Fig. 2. Whether that concerns positive or negative moderation is not evident. As new services often originate from tuning existing offerings to a particular customer's needs, a high degree of customization may provide more opportunities for firms to effectively utilize customer feedback (Sundbo 1997; Bettencourt et al. 2002). Studies like the recent one by Cabigiosu and Campagnolo (2019), however, show that innovation-based performance is not per se higher for customer-oriented firms providing customized services. A possible explanation would be that a sizeable commitment to particular customers' needs leads service providers to adopt a restricted view of diversification possibilities (Danneels 2003; Corrocher et al. 2009). Then again, this leaves unclear why such risk would

only threaten customizing service providers, and not their less-customizing or non-customizing counterparts. After all, service providers deploying a more standardized offering are inherently endowed with ample amounts of rich customer feedback. As Voss and Hsuan (2009) have stated, non-customizing service providers still need to be able to harvest signals that can help them to introduce modified or new modules.

From a dynamic capability perspective, it is important to consider that sensing signals is only the first step in a process also entailing the seizing of observed opportunities (e.g. by altering the business model) and reconfiguring the organization accordingly (Teece 2007). Firms operating in highly customized product environments might start seizing and reconfiguring as soon as they obtain useful signals, whereas firms in standardized product environments typically are more restricted in the amount and scope of modifications they can implement in their organization or offerings. Indeed, one might wonder whether this constraint then requires non-customizing service providers to rely less, or possibly even more, on capabilities for collecting and analysing the customer feedback they encounter.

In sum, existing research only provides partial clues on the nature and direction of the interplay between our focal concepts. Whereas for each aforementioned variable some of the performance-implications are known, these are hard to reconcile with each other in lack of a coherent theory on sensing-related tensions in the face of customization. The complexity of the manifold interactions does not lend itself to be resolved by, for instance, case studies. Thus, to study the coinciding dynamics in a structured way, and to move forward in theory building, we follow the practice of constructing a formal model capturing concepts so far not studied simultaneously (e.g. Puranam and Swamy 2010). Having the framework of interaction modes in place, we now simulate – for both customizing and non-customizing firms – how each of them corresponds to a fundamentally different way of engaging in (and benefitting from) an evolutionary search for novel business propositions.

4 Simulating the different interaction modes

4.1 The NK model of evolutionary search

Assessing the relative benefits of distinct interaction modes requires a theoretically grounded understanding of innovation dynamics. We draw upon evolutionary theorizing on technological and economic change, which regards the development of new offerings as an experimental search process marked by uncertainty (Levinthal 1997; Fleming 2001).

Kauffman's (1993) NK model presents a useful basis for studying (service) innovation as a matter of introducing changes in a multidimensional design spaces (Anderson et al. 1999; Chae 2012b). Firms can pursue better services by changing the design options ('alleles') of one or more dimensions ('genes'). 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 dimension. In the long run, experimentation can be

expected to identify which combination of dimensions delivers the highest fitness, i.e., the global optimum. The extreme opposite of a smooth fitness landscape is a rugged one (Levinthal 1997), in which interdependencies between all dimensions exist ($K=N\text{-}1$). In such a design space, a mutation in one dimension will affect the fitness of all other dimensions, be it positively or negatively. The many local optima in such a rugged 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) can firms reach higher local optima or even the global optimum of the fitness landscape in question. When applied in the context of studying strategic decision making on for instance innovation, it is usually assumed that managers are not aware of how changing one dimension in a rugged landscape will affect the total fitness. Decision makers might have an initial representation of the design options and interdependencies in the landscape they are facing, but whether or not this actually improves search outcomes is by no means evident (Puranam and Swamy 2010).

Applying the NK model in the context of services is not a straightforward exercise: defining the dimensions (*N*) of a product is challenging when it is, at least in part, intangible. Earlier contributions in the field of strategic management have studied particular services such as retail stores and airlines, regarding them as systems of interrelated activities (Porter and Siggelkow 2008). Porter and Siggelkow's discussion of Urban Outfitter's success underlines the importance of aligning elements like its 'bazaar-like setting', its inventory levels, and its scarce use of traditional advertising (2008, p. 35). The notion of reconfiguring activity systems is consistent with understanding service innovation as a process of recombining various elements, as emphasized also by other scholars applying an evolutionary perspective to service innovation (Chae 2012a, b). Desmarchelier et al. (2013), for instance, base their agent-based model for studying service firms' eco-innovations on the characteristics approach of Gallouj and Weinstein (1997). This approach conceptualizes services as the result of mobilizing different sets of product and service characteristics as well as producer and user competences (Gallouj and Weinstein 1997). Service innovation may accordingly be understood as introducing changes in one or more characteristics (Windrum and García-Goñi 2008). Here we follow Janssen and Den Hertog (2018) and Chae (2012b) in taking six dimensions (*N*=6) as a basis for our model, acknowledging that it is also possible to extend this somewhat arbitrary number.

An additional feature to specify here is degree of interdependencies in a design space (*K*), which in fact is closely linked to the core issue of customization. According to the aforementioned characteristics approach, services rely on competences activated by both the service providing firm as well as the customer (Gallouj and Weinstein 1997). In this perspective, standardization consists of making services independent of variation in why and how customers will be using them. For customized services, however, the value that is created depends very much on which specific preferences, capabilities or resources the customer can contribute. Variability on this account poses constraints when thinking about how to design a service, as a firm will have to adapt its own competences (and service characteristics) in order to produce the desired solution. Customization thus poses additional interdependencies compared to a non-customized service, as a customized service

requires a very specific configuration to be able to provide a very specific service. In NK terminology, customizing services implies a higher K-value. Indeed, for the most customized service, the values of all characteristics are mutually dependent for the end user who requires a unique and tailor made solution.

4.2 Notation of the NK model

We denote $n \in \{1..N\}$ the dimensions of the model, and $q \in \{1 \ldots Q\}$ the alleles of each dimension. And, $w_{n,q}$ is the fitness of allele q in dimension n. For $K = 0$, this fitness is independent from the other dimensions, while for $K > 0$, it will depend on the alleles present in the dependent dimensions. The final fitness W of a particular design configuration is the average of the fitness of each dimension. The attractiveness of changing dimension n is X_n, and the attractiveness of changing the allele in dimension n to allele q is $X_{n,q}$. Finally, $P_{n,q}$ is the probability of a mutation to allele q in dimension n.

4.3 Translating interaction modes into search strategies

Our starting point for modelling search strategies is determining the probability P that a firm will mutate by selecting allele q on dimension n. This probability is determined by the attractiveness X of changing a particular dimension (X_n) or even a particular position in the landscape ($X_{n,q}$), depending on the information agents have at their disposal. Following Fig. 1, we distinguish four modes of interaction between service providers and their customers by cross-tabulating two aspects: whether the customer files a complaint or requests a specific improvement, and whether the firm has a strong sensing capability to deal with customer feedback or not.

The first distinction, between complaint and request, can be modelled by distinguishing between *extremal search* and *greedy search*. In search theory, extremal search implies a mutation in the worst performing dimension of a search space by randomly picking another allele along this dimension. Within our particular research setting this reflects the effect of a complaint as a form of feedback, indicating bad performance without showing the kind of improvement that should be made (i.e. without indicating which allele should be chosen). Greedy search, by contrast, implies that a particular new allele is chosen that maximizes the fitness improvement along a dimension. This form of search is still local since it chooses the allele that brings the largest fitness gain on a single dimension, rather than maximizing the overall fitness. Yet, it assumes that the firm has received very precise feedback from its customers to implement a specific allele along a specific dimension. For the sake of simplicity, we assume that different customers are consistent in their feedback; it is merely the level of detail that can differ.

The two forms of customer feedback determining a mutation's attractiveness are implemented as follows. If customers complain about dimension n, which has at the

Fig. 3 Operationalization of search strategies for each interaction mode
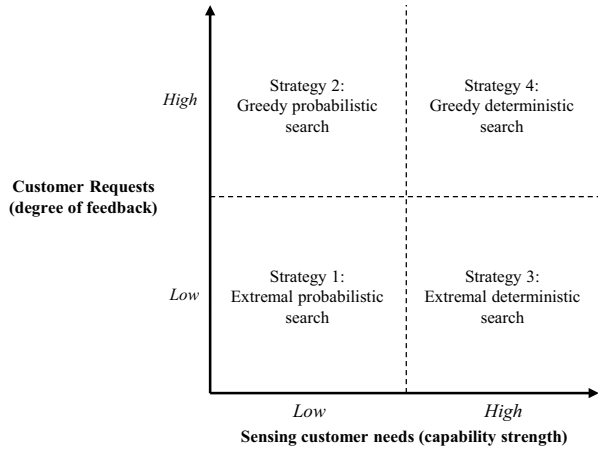
moment allele r, the attractiveness of changing this dimension is $: X_n = 1 - w_{n,r}$. If customers provide a specific request of mutating dimension n from allele r to allele q, the attractiveness of this mutation is $: X_{n,q} = w_{n,q} - w_{n,r}$.

The firms themselves can follow two strategies. Firms with a well-developed sensing capability are able to identify the most promising customer feedback. Then, they chose the most attractive mutation with probability 1. We call this strategy a deterministic search.

When a firm has only a moderate sensing capability for monitoring customer suggestions, the chance of a mutation being selected is proportional to the relative attractiveness of encountered inputs. The resulting probability of the different mutations for firms with moderate sensing capabilities is $P_{n,q} = X_{n,q} / \sum_{m,r} X_{m,r}$. We call this strategy a probabilistic search.

In Fig. 3, we summarize the search strategies that correspond to the interaction modes.

4.4 A detailed example of the search strategies in a small landscape

In this section we show a step-by step example of how the search strategies work in a smaller landscape, with $N = 3$ dimensions and $Q = 3$ possible alleles for each dimension. Appendix Table 5 shows the fitness of all possible combinations of alleles. For $K = 0$ (left-hand matrix), there are no interdependencies between the dimensions: the overall fitness depends exclusively on the fitness change of the dimension that is being mutated. When interdependencies are present, changing one dimension will also affect the fitness of alleles in other dimensions. The matrix in the middle and right-hand side of Appendix Table 5 illustrates how this would work for $K=1$ and $K=2$, respectively. Note that for different values of K, the entire landscape is reinitiated (hence, the different fitness values for the strings 000).

The landscape for $K=0$ has a global optimum, string 111, which can be reached by sequences of mutations from anywhere in the landscape. For $K=1$, there is also

a local optimum. Any single mutation from string 021 will always lead to a lower fitness; firms following the strategies of only mutating in case of improvements will, therefore, never reach the global optimum of string 110 once they have arrived at the local optimum. When $K=2$, there are even four optima, string 011 being the global optimum.

To illustrate the four search strategies that we distinguish, consider an agent that starts from position 000 in the landscape of $K=1$.

If the customer feedback is low, an agent will only observe the 'attractiveness-values' shown in Appendix Table 6 for the landscape in which $K=1$ (based on $X_n = 1 - w_{n,r}$; values for $w_{n,r}$ are underlined).

The case of **extremal deterministic search** (high sensing capability level) implies that a firm only uses feedback to determine which *dimension* to change; in this case, dimension *n2*, which is the worst performing dimension. Hence, the firm will randomly mutate the second dimension into either state *q1* or state *q2*. The chance *P* of picking these alleles is equal for all states *q* on the worst dimension *n*.

In the case of **extremal probabilistic search** (low sensing capability level), the probabilities for selecting a certain dimension for mutation in the landscape with $K=1$ are a function of the relative attractiveness values, as shown in the right column of Appendix Table 6. The sum of all these probabilities is 1. Furthermore, this extremal search strategy will only tell agents which dimension *n* to pick; they will still have to mutate the selected dimension randomly to a different state *q*.

If customer feedback is high, the search procedure is more advanced. The attractiveness now depends on the fitness increase that occurs at a certain dimension when adopting a particular suggested *allele*. In Appendix Table 7, we consider again the fitness landscape for $K=1$ to illustrate the effect of interdependencies in the design space.

If the starting point for agents is still string 000, there are six strings that can be selected when making one single mutation: on each of the dimensions n1, n2 and n3 the agents can choose to change *q0* into *q1* or *q2*. From the possible mutations shown below, string 020 would denote the biggest fitness increase along an individual dimension (+0.6 at dimension n2). Hence, **greedy deterministic search** would imply that the firm mutates the second dimension into state 2, leading to string 020 (note here that a mutation into state 1, leading to string 010, would yield better overall results in terms of total fitness W).

Greedy probabilistic search, then, is based on the probabilities that can be obtained by comparing the relative fitness increases that agents achieve when optimizing individual dimensions. These probabilities are shown in the last column of Appendix Table 7.

4.5 Simulation procedure

In order to run the simulation models, we use Kauffman's NK model as introduced in 1993. According to our earlier assumptions, in a design space with six dimensions ($N=6$), the interdependencies can be calibrated at $K=0$ for standardized services

and at a higher level ($K > 0$) for customized services. 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. $Q = 10$, $Q = 20$). The fitness values for each string of dependent dimensions are drawn from a uniform distribution $U[0, 1]$.

Once a design space is created, we run a simulation for all four search strategies. Using the chances $P_{n,q}$ to make a draw from a uniform distribution leads on to the actual selection of a mutation. Each simulation consists of a number of consecutive search steps. Finally, to avoid conclusions based on exceptional runs, we repeat the entire procedure 100 times.

4.6 Simulation results and hypotheses formulation

As the direct merits of sensing customer needs and customer feedback may be obvious from the outset, the true value of the simulation lies in revealing how the combination of these factors differs for various values of K. Inspection of the simulation results (Fig. 4) shows that the most important patterns become clear within approximately 20 steps. Based on these simulation results, we formulate our hypotheses.

First, the simulations for $K = 0$ represent the situation in which complexity is absent. This occurs when services are standardized in such a way that different design options can be chosen for each of the business model dimensions, without affecting the other ones. Non-customizing agents following the extremal probabilistic strategy have the lowest take-off in their fitness increase. The opposite strategy of greedy deterministic search, in which both high levels of customer feedback and strong sensing capabilities are present, is vastly superior. Better listening and receiving more signals apparently reinforce each other when used to improve business model aspects not influenced by other dimensions.

Hypothesis 1: For non-customizing service providers, the strength of their sensing customer needs capability and the intensity of customer requests have a positive interaction effect on innovation success.

Services not entirely standardized leave greater opportunities for customization. However, this typically implies that ad-hoc adaptations in one dimension lead to (or require) adaptations in another non-standardized dimension. When at least some dimensions are interrelated, a different order in strategy pay-off performance emerges.

For the greedy deterministic strategy, the value of sensing would appear to be of short duration only. Despite initially having a high fitness quotient (i.e. fitness increase per step), all graphs with $K \geq 1$ show that the maximum achieved fitness level for the greedy deterministic strategy stabilizes after a few mutations. Apparently, when customizing agents are exposed to detailed feedback (including information on unmet needs and the perceived quality of a firm's service), and when they have a strong ability to analyse customer needs thoroughly, there is the risk of ending up in a local optimum. This finding is largely due to the fact that such agents
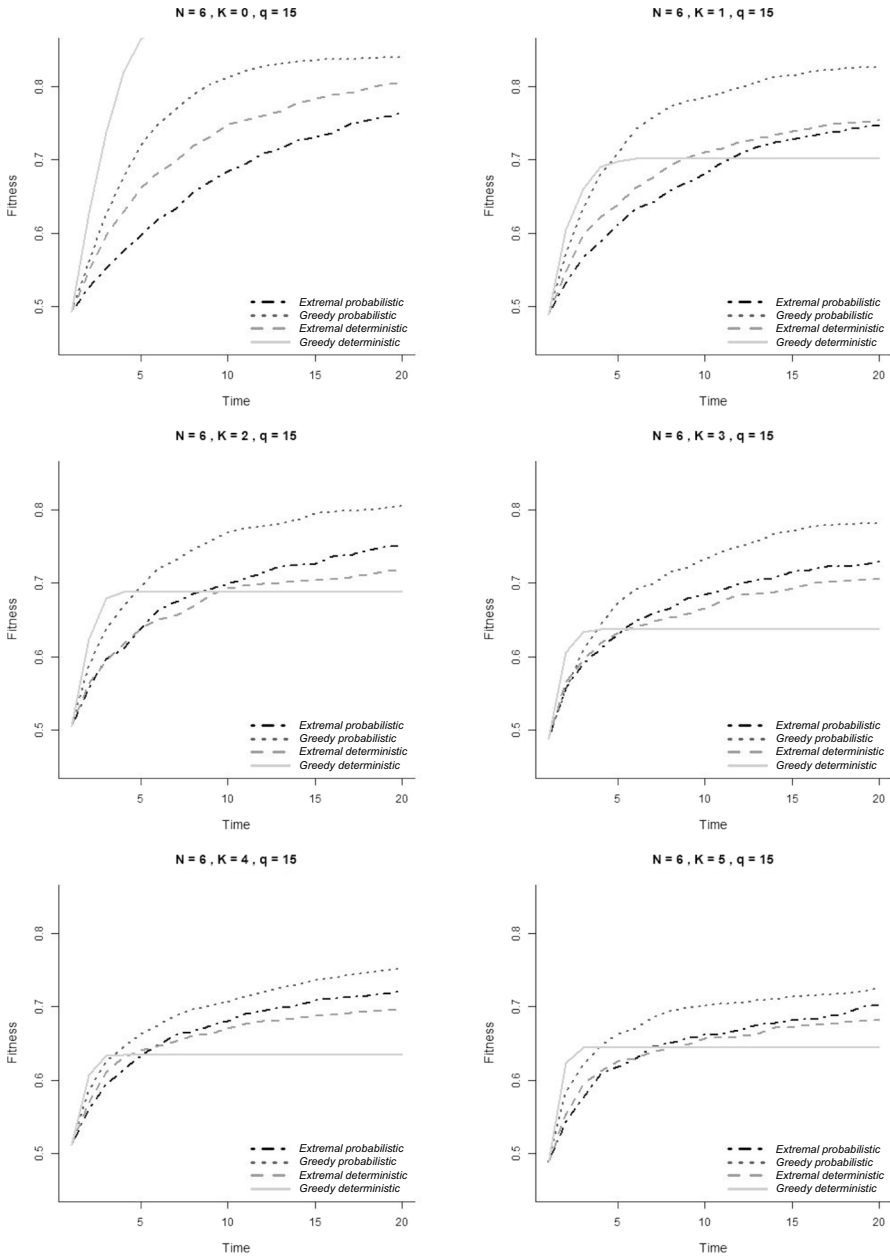
Fig. 4 Maximum achieved fitness levels for different levels of K. N = 6, q = 15

respond to urgent customer 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 deterministically reacting to needs related to specific dimensions. Additional mutations rarely yield a fitness increase. Agents who do not rely heavily on sensing, such as those following the probabilistic strategies, prove to have a higher chance of experimenting with mutations suitable for subsequent tweaking and tuning.

In sum, for customizing firms exposed to a large number of requests, the comparative advantage that can be derived from the sensing capability is thought to diminish as they may become tempted to focus excessively on the needs their current customers are experiencing. Fulfilling those needs improves the existing product for the existing market, but it may not be the optimal choice for introducing services capable of delivering even greater value than those based on 'fixing' complaints. While agents (in $K > 0$ landscapes) with an extremal deterministic strategy keep achieving higher fitness levels over time, this does not hold for agents who follow the greedy deterministic strategy. Agents in the latter situation tend to reach a local optimum that is below the fitness levels other agents achieve. Therefore, we would expect that the combination of having a strong sensing capability and facing extensive customer feedback has an adverse effect on the innovation performance of customizing service providers.

Hypothesis 2: For customizing service providers, the strength of their sensing customer needs capability and the intensity of customer requests have a negative interaction effect on innovation success.

5 Empirical examination

5.1 Methodology

5.1.1 Survey

We examine our hypotheses with a dataset based on a survey deployed in 2011. Items in the questionnaire covered a variety of topics, including general company characteristics, innovation types, innovation success, dynamic capabilities, innovation processes, innovation partnerships, innovation barriers, and market environment. The majority of the items were retrieved from existing scales. The questionnaire has been subjected to rigorous pre-testing procedures, including feedback collection from academic peers as well as respondents. In general, most items make use of a 7-point Likert scale ranging from 'strongly disagree' to 'strongly agree'. The measures for variables used in this study are discussed below.

5.2 Sample

The survey sample consisted of single-business firms or business units with more than 10 full-time employees. Using databases from Bureau van Dijk, we retrieved

contact information from Dutch firms located in the Northern Randstad (i.e. the Amsterdam Greater Region and the Utrecht Greater Region). 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 of 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 of completion via the web if preferred. We obtained responses (some of them incomplete) from 458 unique firms, which amounts to a response rate of 5.69%. As the survey was of considerable length, and the sample had no particular relation to 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 survey distribution revealed that a large proportion of the addresses were outdated; out of 100 non-respondents contacted by phone, about half were either no longer active in the same function or no longer contactable at the address the survey was directed to. A non-response analysis shows that there are only minor differences in the demographic characteristics of respondents and non-respondents, suggesting that the final response is largely representative of the sampled population.

Given the scope of our study, we only look at firms that completed the survey questions relevant for the variables in our analysis. Moreover, out of these 355 firms, we select the ones that are somehow involved in providing services. This might concern anything from pure service firms to servitized manufacturers offering services around or instead of a physical product. An indication of the extent of service provision is given by asking respondents whether they have substantial turnover stemming from services; those with no revenues from that source (scoring below the middle of the Likert-scale) are omitted from the current analysis. This non-service group accounted for 18% – just a small percentage of our representative sample. The final subsample contains 292 complete cases, most of them serving a relatively high number of customers via labour-intensive processes in a predominantly business-to-customer setting. The mean and median firm age are 26 years and 18 years, respectively. Table 1 provides the industry category distribution of the 355 firms with complete data as well as the 292 ones providing services. Both groups have a similar industry composition. Firms reporting turnovers from service provision have an overrepresentation of Professional, Scientific and Technical Activities (28% vs. 24%), and an underrepresentation in the categories Wholesale, Retail Trade, Repair of Motor Vehicles and Motorcycles (13% vs. 19%) and Manufacturing (6% vs 9%).

Crucially important here is the distinction between firms who do or do not adapt their services to the needs of individual customers. As the customization degree of a firm's offerings is hard to modify on the short term, we investigate the interaction effect of sensing customer needs and customer requests in two sample groups (following Janssen et al. 2018) representing distinct types of business environments. Figure 5 shows the distribution of responses to the question whether firms in the sample customize their services. Most of our respondents appear to be heavily engaged in customization, which is hardly surprising if

Table 1 Industry composition of survey respondents

Industry Category	All completed responses (n=355)	Service providers (n=292)
Agriculture, Forestry and Fishing	1%	1%
Manufacturing	9%	6%
Electricity, Gas, Steam and Air Conditioning Supply	0%	0%
Water Supply; Sewerage, Waste Management and Remediation Activities	1%	2%
Construction	8%	9%
Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	19%	13%
Transportation and Storage	5%	5%
Accommodation and Food Service Activities	2%	2%
Information and Communication	11%	12%
Financial and Insurance Activities	5%	5%
Real Estate Activities	3%	4%
Professional, Scientific and Technical Activities	24%	28%
Administrative and Support Service Activities	5%	5%
Education	1%	1%
Human Health and Social Work Activities	4%	5%
Arts, Entertainment and Recreation	2%	2%
Other Service Activities	1%	1%

Fig. 5 Distribution of answers to the statement: "Our services are customized", on a 7-point Likert scale
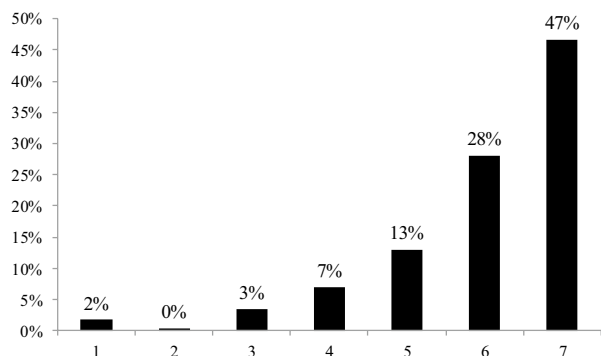
one realizes that meeting individual customer requests is often seen as an inherent part of providing services. Nevertheless, some firms declare that they customize their services only to a limited extent. To make a distinction between our two focal groups, while preserving group sizes allowing for statistical analyses, we consider customizing service providers as consisting of the 218 cases scoring
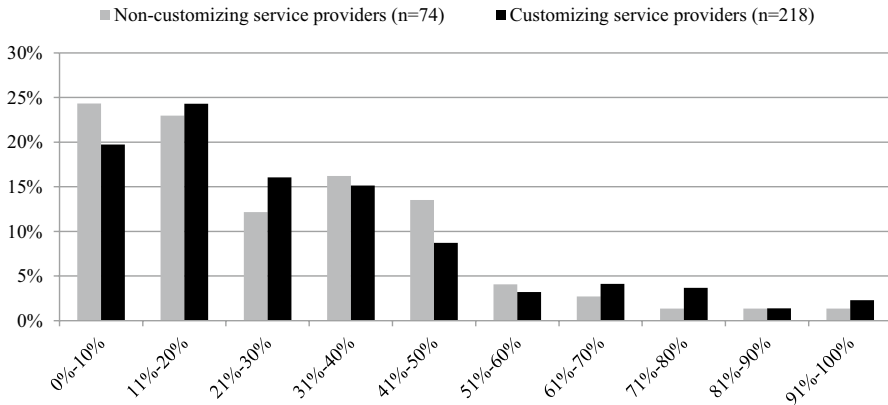
Fig. 6 Distribution of dependent variable (% of turnover stemming from improved or newly introduced offerings)

a 6 or 7 on the ordinal Likert-scale. The remaining cases account for 25% of our final sample.

5.2.1 Variables

The variables included in our statistical analysis mirror the factors underlying the simulation models from which we derived the hypotheses. Accordingly, for both customizing and non-customizing service providers, we aim to predict innovation performance by assessing the direct and interaction effects of having a sensing customer needs capability and receiving customer feedback.

The dependent variable of innovation performance 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 2005), these products can be services, goods, or any combination thereof. What matters in this study is that a firm is at least engaged to some extent in 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 Fig. 6), ranging between 0 and 100%, relations between our variables are assessed with multivariate Tobit regression models (Laursen 2011).

As for the independent variables, Den Hertog et al. (2010) introduced sensing customer needs as a crucial dynamic capability for realizing innovation in a services context. Being essentially a dynamic capability (Teece and Pisano 1994), the strength of a firm's ability to sense customer needs depends on whether it has structured (but not necessarily formalized) routines in place for staying aware of its customers' needs. 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 to different capability levels or strengths. The capability conceptualized

by Den Hertog et al. (2010) has been constructed and applied accordingly by Janssen et al. (2016). The survey items we adopt are as follows:

- 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.

Again, we take the average of the underlying three items as a measure of the strength of this capability.

The item for Customer Requests ("Our clients regularly ask for new goods and services") stems from work by Jansen et al. (2006), and serves as a proxy for the quality of the feedback a firm is confronted with. When customers often ask explicitly for new services, they may provide detailed information on which aspects of an offering to modify (nurturing the greedy strategies). In case firms face no or just a low level of requests, they can only base their entrepreneurial experimentation on the complaints they receive during regular service delivery. Both independent variables resemble a normal distribution.

5.2.2 Statistical models

Our split model estimation strategy consists of running distinct multivariate Tobit regression analyses for the sample of non-customizing service providers (the baseline model) and the sample of customizing service providers. Using hierarchical modelling, we first include both independent variables in our regression models before extending it with an interaction term. Such an analysis sheds light on the combined effect of sensing customer needs and customer requests along all values that both variables can take. In this analysis, however, we are especially interested in the question whether sensing customer needs can have an adverse effect when firms are exposed to high levels of customer requests. Following Spiller et al. (2013), we also conduct a so-called 'floodlight analysis' to examine at which particular values for customer requests a possible interaction effect occurs. This analysis consists of replacing the continuous 'customer requests' variable for a binary dummy, and running the regression model for all possible cut-off values (on the 7-point Likert Scale) for creating this dummy.

To control for the fact that customer 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 also used as a control variable, similar to a construct ('R&D formalization') that indicates the extent to which a firm has well-established R&D efforts.[1]

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[1] Looking at the number of observations, the risk of saturation requires us to minimize the amount of control variables. If we include variables for 'labour intensity', 'number of customers' or' market type' (B2C/B2B), all results remain similar.

Table 2 Descriptive statistics and correlations (in italics) for both groups of service providers

Total sample (n=292)	Mean	Std. Dev	C1	C2	C3	X1	X2	Y
C1. Firm size (log fte)	3.49	1.237						
C2. R&D formalization	3.53	1.312	*.043*					
C3. Market dynamism	5.41	1.400	*-.005*	*.088*				
X1. Sensing Customer Needs (S.C.N.)	4.68	1.167	*.064*	*.400*****	*.157***			
X2. Customer Requests (C.R.)	4.49	1.606	*.018*	*.277***	*.563***	*.279***		
Y. Turnover from new or improved offerings (%)	32.23	22.259	*-.047*	*-.007*	*.140**	*.172***	*.268***	
Non-customized service providers (n=74)	Mean	Std. Dev	C1	C2	C3	X1	X2	Y
C1. Firm size (log fte)	3.69	1.440						
C2. R&D formalization	3.69	1.251	*.037*					
C3. Market dynamism	5.28	1.429	*.027*	*-.057*				
X1. Sensing Customer Needs (S.C.N.)	4.63	1.153	*-.003*	*.532***	*-.037*			
X2. Customer Requests (C.R.)	4.65	1.548	*.158*	*.104*	*.554***	*.186*		
Y. Turnover from new or improved offerings (%)	3.27	21.512	*.065*	*-.081*	*.139*	*.191*	*.213**	
Customized service providers (n=218)	Mean	Std. Dev	C1	C2	C3	X1	X2	Y
C1. Firm size (log fte)	3.42	1.156						
C2. R&D formalization	3.47	1.331	*.037*					
C3. Market dynamism	5.45	1.391	*-.011*	*.140**				
X1. Sensing Customer Needs (S.C.N.)	4.70	1.173	*.097*	*.363***	*.221***			
X2. Customer Requests (C.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***	

$^{*}=p<.0.05$, $^{**}=p<.01$

The described estimation strategy can be summarized as running the following equations, for both the non-customizing firms (Models 1–3) and the customizing firms (Models 4–6). The variable 'Customer requests (dummy)' is based on different cut-off values in the aforementioned floodlight analysis design.

Model 1 and 4 : $Y = \beta_0 + \beta_1 * Sensing\ Customer\ Needs + \beta_2 * Customer\ Requests\ (continuous) + [\beta * Control\ variables] + \varepsilon.$

Model 2 and 5 :
$$Y = \beta_0 + \beta_1 * Sensing\ Customer\ Needs + \beta_2 * Customer\ Requests\ (continuous) + \varepsilon.$$
$$+\beta_3 * S.N.C * C.R[\beta * Control\ variables]$$

Model 3 and 6 :
$$Y = \beta_0 + \beta_1 * Sensing\ Customer\ Needs + \beta_2 * Customer\ Requests\ (dummy) + \varepsilon.$$
$$+\beta_3 * S.C.N * C.R(dummy) + [\beta * Control\ variables]$$

Table 2 shows the descriptive statistics of the variables in our models. None of the differences between the customizing and non-customizing firms (with respect to

Table 3 Regression results for baseline model with sample of non-customizing service providers ($n = 74$)

Y = % turnover from improved / new offerings	Model 1		Model 2		Model 3	
	Beta	(Std. error)	Beta	(Std. error)	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)
R&D 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 Customer Needs (cont.)	5.650**	(2.454)	-7.880	(6.939)	1.339	(2.940)
Customer Requests (cont.)	2.009	(1.910)	-9.856	(6.009)		
S.C.N.*C.R			2.726*	(1.313)		
Customer Requests (binary)[a]					-29.894	(19.715)
S.C.N.*C.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 customer requests, threshold is ≤ 5 (C.R. $= 0$) versus > 5 (C.R. $= 1$). See description of floodlight analysis

variable means) is statistically significant. At the outset, both groups are on average equally innovative, encounter a similar degree of feedback, and have similar capability strengths. As there are no high correlations between the variables (all variance inflation factors are well below 3), none of them needs to be excluded from our models.

Finally, we address validity risks due to unobservable factors (e.g. certain managerial capabilities) influencing both a firm's sensing user needs capability and its innovation success. To account for omitted variable bias we conducted a Durbin-Wu-Hausman endogeneity test, which requires an instrumental variable that is highly correlated with a potentially endogenous construct but not overly correlated with the dependent variable (Wooldridge 2010). A suitable option here is a survey item asking respondents whether their organisation deliberately reflects on its innovation activities. Such self-reflexivity can be regarded as a meta-capability that is essential for developing innovation capabilities for e.g. sensing user needs (Den Hertog et al. 2010; Janssen et al. 2016). Precisely because of being a meta-capability, however, the relation with eventual innovation success is likely to be more indirect and thus weaker. Including the self-reflexivity variable as an instrumental variable in the Durbin-Wu-Hausman test shows that the null hypothesis can not be rejected (p = 0.5663), suggesting that this study is unlikely to suffer from endogeneity issues due to omitted variable bias.

5.3 Baseline: Regression results for non-customizing service providers

Table 3 presents the regression analyses for the sample of non-customizing firms, starting with the model that involves only control variables and direct effects

(Model 1). Although market dynamism is strongly related to customer requests, this control variable is not significantly related to turnover from innovation. The contrary holds for formalization of innovation efforts, which captures to what extent innovation activities follow a deliberate, explicit and systemic approach. Its negative direction is consistent with the general finding that many service providers 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 such as dynamic capabilities is a suitable option for analysing how service providers achieve innovation success.

It is noteworthy that, for non-customizing service providers, only the independent variable of sensing customer needs appears to be of significant value. Receiving customer requests by itself is not associated with a stronger innovation performance. Note, however, that the overall model is only weakly significant. If we include the interaction term for sensing customer needs and encountering requests (Model 2), the overall model fit improves to $p < 0.05$. Both independent variables significantly reinforce each other.

The interaction effect, confirming hypothesis 1, is obtained when both continuous independent variables are multiplied. Since the mechanisms we hypothesized concern the interaction effect of sensing customer needs (S.C.N.) at particularly high values of customer requests (C.R.), we continue by decomposing the interaction (Spiller et al. 2013). To do so, we dichotomize the customer 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.C.N. and C.R. at the full range of C.R.'s cut-off values.[2] Jointly, the spotlight regressions comprise 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 already appears when C.R. reaches a value of 4, while the positive interaction becomes more significant when placing the cut-off at $C.R \geq 5$ (results shown in Model 3). Non-customizing service providers thus leverage the value of their sensing-customer-needs capability especially when facing abundant customer requests. The more there is to respond to, the better they seem able to introduce turnover-improving innovations.

5.4 Regression results for customizing service providers

Turning to the results for customizing service providers, Table 4 sketches a different picture. Sensing customer needs again has a (weak) positive effect on the turnover appropriated from innovation but, this time, the requests themselves appear to be strongly related to innovation-based turnover. In accordance with the simulation results, the beta coefficients and significance levels in Model 4 indicate that this effect is even somewhat larger compared to having a strong sensing capability.

Model 5 reveals that the interaction term of both continuous variables is weakly significant and has a negative direction. This also holds in a robustness test in which

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

Table 4 Regression results for sample of customizing service providers ($n=218$)

Y = % turnover from improved / new offerings	Model 4		Model 5		Model 6	
	Beta	(Std. error)	Beta	(Std. error)	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)
R&D 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 Customer Needs (cont.)	2.580*	(1.360)	8.539**	(3.530)	4.958***	(1.538)
Customer Requests (cont.)	4.410***	(1.146)	10.903***	(3.676)		
S.C.N.*C.R			-1.373*	(0.739)		
Customer Requests (binary)[a]					52.563***	(14.516)
S.C.N.*C.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 customer requests, threshold is ≤ 5 (C.R.=0) versus > 5 (C.R.=1). See description of floodlight analysis
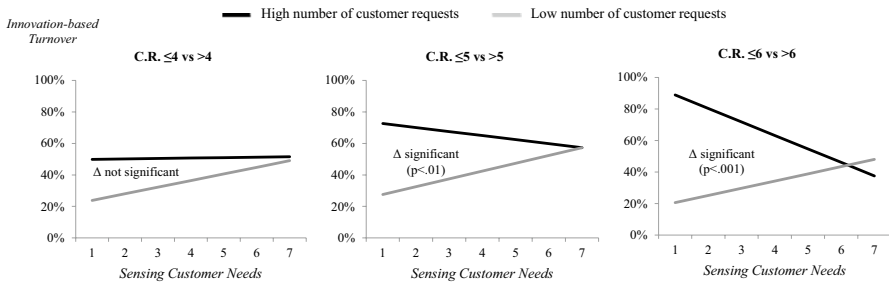
Fig. 7 Visualization of regression parameters for customizing service providers, based on different thresholds for customer requests (C.R.). The negative moderating effect of C.R. (i.e. difference between the slopes) is only significant when the threshold lies at C.R.≥ 5

we compare only the most customizing service providers (scoring a 7 on the Likert-scale) against all other firms in our sample. As the significance of our main result is somewhat low, we conduct an extra test to ensure that the interaction effect is truly different from the structural effects caused by the non-linear nature of our model (Ai and Norton 2003). Bowen (2012) provides a procedure for assessing the 'secondary' effect caused by the actual interaction effect. Applying his Stata-code shows that the 95% confidence interval stretches from -2.535 to 0.056, implying a secondary model fit of $p=0.061$. Furthermore, the floodlight analysis reveals that, for customizing firms, the positive interaction starts to be significant when C.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 C.R. = 5 do not yield a significant interaction (only the direct effects of S.C.N. and C.R. are significant and positive), while the two models above this point confirm that sensing customer needs combined with ample customer requests has a significant and negative relation to innovation-based turnover. Model 6 presents the results for C.R. threshold = 5 (the model with the threshold at 6 even has an interaction term with significance at the level of $p < 0.001$). This time the secondary effect's 95% confidence interval is well below zero, ranging from -12.484 to -2.166 ($p = 0.005$). The results of the floodlight analysis are also visualized in Fig. 7, clearly showing that firms facing only a small number of requests benefit from having a strong sensing capability. The contrary holds for firms more often exposed to customer requests: generally, their innovation-based turnover is relatively high, but this decreases as firms start to rely more on their sensing capability. Hypothesis 2 can thus also be confirmed, especially in case of high degrees of customer requests.

6 Discussion

6.1 Conclusions

Aimed at contributing to scholarly debates on the use of customer feedback in innovation processes (Lundvall 1988; Chatterji and Fabrizio 2012; Sundbo et al. 2015), this paper provides an argument on why investing heavily in a sensing capability may have adverse effects even (or especially) on customizing service providers for whom feedback is of vital importance. So far, little sustained effort has been applied to understanding how exactly the deliberate response to customer requests enhances or undermines the success of their search processes (Chatterji and Fabrizio 2014; Bogers et al. 2010).

We examined the extent to which the benefits of openness to customer insights depend on the behaviour of a customizing firm's customers and, in particular, whether explicit requests for new services can make a strict sensing capability a strategic weakness rather than a strength. The findings from our simulations and empirical tests point in similar directions. Listening carefully to demanding customers is useful in identifying the most efficient and immediate improvements, but a heavy reliance on sensing feedback in all its manifestations places over-zealous innovators at risk of becoming stuck in a suboptimal configuration in the longer run. This finding is similar to Knudsen and Srikanth's (2014) observations on 'joint myopia' occurring when firms engage in search together with other actors, except for that we demonstrated the myopia to emerge when customers only provide feedback rather than taking part in the search process itself. Firms who tailor their services to demanding customers might be tempted to focus strongly on encountered needs and, therefore, go down an unfruitful path of 'local optimization'. Such excessive attention to their customers can prevent them from seeing opportunities to introduce genuinely new improvements or commercializing services in other contexts. As a consequence of this over-sensing and over-serving, the firm may well find itself left with a set of competences and skills

suitable for serving only a very restricted market segment. The resulting paradox is that those firms that are most engaged in fulfilling actual customer needs – customizing services providers – might well be the ones that (in terms of innovative performance) benefit less from developing a capability for sensing customer needs.

The caveat of over-pleasing customers has been discussed extensively for markets typically concerned with series of relatively standardized products (King and Baatartogtokh 2015). New products based on customers' stated needs may be short-lived, either due to evolving needs or due to competitors quickly improving the original (e.g. Narver et al. 2004; Querbes and Frenken 2017). We now highlight a similar but distinct pitfall for customizing service providers. This particular segment of firms, unlike product-only firms, typically does not risk tailoring a uniformly produced offering to the demands of just a small market. Many customizing service providers never attempt nor manage to conceptualize ad-hoc solutions into replicable business propositions (Sundbo 1997). The reason their innovation performance can continue to suffer from a combination of strong capabilities and plentiful customer requests is, in our view, that pursuing particular customers' needs comes at the cost of neglecting other signals or stifling innate creativity. Obtaining inspiration from customers might be useful, but not when it produces commercial short sightedness. Consistent with this explanation, adding an alternative view to the literature on myopia, is our finding that non-customizing service providers do not experience any adverse effects from having strong sensing customer needs capabilities. Most likely, the latter group is more inclined to weigh feedback carefully when deciding upon which standardized feature to introduce.

The conjunction of particular feedback signalling and sensing behaviours can thus create a major drawback, depending on the type of service that is being provided. So far, the research concerned with customization in relation to services and innovation has paid little attention the possibility that continuously customizing intangible services might prevent firms from taking proper stock of all the signals they have been sensing (Tether et al. 2001; Ding and Keh 2016; Cabigiosu and Campagnolo 2019). Besides the threat of second-mover action, it is also the way a firm deals with rich feedback that inhibits the innovation potential of utilizing customer-based signals. Our research suggests that the very tailoring of services, despite being the key to obtaining valuable customer feedback, can in fact distract customizing firms from exploring new services that meet widely shared demands.

6.2 Managerial implications

For firms that customize their services to encountered customer requests, a short-sighted focus on introducing quick-win incremental changes must be seen as a serious caveat: they run the risk of being saddled with innovations Lundvall would classify as 'unsatisfactory' (1988). If we accept Rosenberg's (1969) classic notion of customer needs as a focusing device, we should nevertheless warn managers against using it rashly. Earlier research already established that a responsive market orientation can hamper product success (Slater and Narver 1998; Narver et al. 2004;

Frishammar and Hörte 2005), but so far it has been scarcely acknowledged that particularly customizing service firms might miss out on market opportunities not addressed by customers themselves. In order for such firms to keep improving their competitiveness, it is surely wise to engage in experiments that are not exclusively based on the customers' own (more or less detailed) ideas of what a viable adaptation of the current offering should be. That is, especially customizing service providers facing high degrees of rich customer feedback are advised not just to rely on their sensing customer needs capabilities, but also to get ideas and inspiration from other knowledge sources, like suppliers, competitors, or universities.

Pointing to the importance of overcoming excessive local search (Rosenkopf and Almeida 2003; Laursen 2012), this paper offers an explanation for findings such as the conclusions presented by Laursen (2011) who observes that innovation performance is negatively affected when firms fail to complement intensive user-producer interaction with sourcing other knowledge channels. Accordingly, we endorse the claim that service providers benefit more from investing in other aspects of knowledge generation and application than concentrating their efforts solely on intensifying user-producer interaction (Mina et al. 2014; Janssen et al. 2018).

Since intense customer interaction is an inherent characteristic of providing services, our investigation is largely focused on firms that co-produce with their customers partly intangible offerings. However, we have no reason to believe that our results are exclusive to service providers: this study can also inform specialized suppliers who, by tailoring technologies to variegated customer needs, correspond to the pure manufacturing equivalent of providers of customized services (Cusumano et al. 2015; Castellacci 2008). For several decades, a trend has been established in which firms increasingly adopt business models based on providing actual solutions and experiences rather than solely shipping standardized artefacts (Chesbrough 2011; Suarez et al. 2013). Although their new business models may still involve technology, competitiveness is mostly derived from the stage at which firm and customer jointly create the desired solution (Anderson et al. 1997; Teece 2010). Therefore, the finding that sensing is of limited relevance under certain circumstances may also be of significance to firms from industries where the urge to 'open up' is strongest (Chesbrough 2011).

6.3 Limitations and further research

Having shed light on the strategic value of sensing customer needs capabilities for service providers, scope has now opened up for further research to examine whether customizing technology providers experience some type of innovator's dilemma when responding to customer requests. Our focus on service characteristics that are becoming prevalent for an increasing number of firms – intense customer interaction and customization – matches on-going efforts to explore how the peculiarities of service innovation hold implications for our general understanding of novelty creation in modern economies (Drejer 2004; Tether 2005; Miles 2007). This study can be regarded as another advance in the line of research that aims to make strategy

and innovation theories – particularly, with respect to openness – more sensitive to the peculiarities of service provision (Gallouj and Windrum 2009; Mina et al. 2014).

By building on recent attempts to conceptualize service innovation as evolutionary search in a multidimensional design space, we have also sought to make a contribution to the currently unfolding debate regarding NK modelling in the context of services (Chae 2012a, b; Desmarchelier et al. 2013; Janssen and Den Hertog 2018). Relying on such models provides a coherent theoretical underpinning for venturing further into the dynamics involved in utilizing external knowledge. The NK-simulations conducted here required sensing capabilities and customer feedback to be translated into archetypical search strategies (extremal and greedy search), in order to inspect how they would interact in more or less customized service environments. The stylized model can now be extended by incorporating the possibility of firms to leave the local optima their search strategy leads them to. Useful inspiration for strategies and product designs allowing agents to escape local optima can be found in Hovhannisian and Valente (2004), Marengo et al. (2005) and the recent review by Baumann et al. (2019). Extended models might also address the influence of heterogeneity in customer preferences, different capability types, management styles, and the use of additional knowledge sources. Exploring how customizing service providers may utilize other types of external knowledge, to avoid the peril of overly pleasing their customers, might be one of the most promising avenues for follow-up research. Furthermore, it appears fruitful to study settings in which customers do not just provide feedback but also actively take part in joint discovery activities; it is not unthinkable that customer's own representation of the search process might affect the provided signals and therefore also the search outcome (Puranam and Swamy 2010).

From a methodological perspective, this paper aspires to advance strategy and innovation studies by responding to the urge for studies bridging the gap between NK models and their empirical implementation (Chae 2012a; Ganco 2017; Baumann et al. 2019). We fully acknowledge that the latter is based on a sparse model and a single source of small sample data only, giving rise to questions on common method bias and endogeneity. Its role in this study should primarily be regarded as a first test of the dynamics we modelled, laying the foundations for in-depth capability analyses in markets with different customization and feedback profiles. To our knowledge, combining model development and survey analysis is of considerable originality to the audience we address. We believe it has the potential to inspire further research on understanding and validating mechanisms where the interaction is unknown at the outset.

Appendix: Tables supporting the explanation of search strategies (section 4.4)

Table 5 Fitness landscapes corresponding to a design space with N=3 and q=3, for K=0 (no interdependencies), K=1 (in this case: n1 n2, n2 n3, n3 n1) and K=2 (all dimensions interdependent). Cells marked in grey denote local/global optima in the fitness landscapes. Based on Kauffman (1993)

K=0	n1	n2	n3	W	K=1	n1	n2	n3	W	K=2	n1	n2	n3	W
000	0.4	0.5	0.2	0.37	000	0.6	0.3	0.5	0.47	000	0.2	0.7	0.8	0.57
001	0.4	0.5	0.6	0.50	001	0.8	0.3	0.7	0.60	001	0.1	0.0	0.9	0.37
002	0.4	0.5	0.3	0.40	002	0.2	0.3	0.6	0.37	002	0.2	0.6	0.2	0.36
010	0.4	0.7	0.2	0.43	010	0.6	0.5	0.8	0.63	010	0.6	0.0	0.2	0.27
011	0.4	0.7	0.6	0.57	011	0.8	0.5	0.4	0.57	011	0.9	0.7	0.8	0.83
012	0.4	0.7	0.3	0.47	012	0.2	0.5	0.2	0.30	012	0.7	0.5	0.2	0.45
020	0.4	0.4	0.2	0.33	020	0.6	0.9	0.1	0.53	020	0.9	0.8	0.2	0.62
021	0.4	0.4	0.6	0.47	021	0.8	0.9	0.5	0.73	021	0.1	0.9	0.5	0.50
022	0.4	0.4	0.3	0.37	022	0.2	0.9	0.7	0.60	022	0.5	0.5	0.5	0.49
100	0.8	0.5	0.2	0.50	100	0.7	0.6	0.5	0.60	100	0.4	0.5	0.4	0.44
101	0.8	0.5	0.6	0.63	101	0.3	0.6	0.7	0.53	101	0.2	0.0	0.2	0.15
102	0.8	0.5	0.3	0.53	102	0.5	0.6	0.6	0.57	102	0.3	0.7	0.3	0.43
110	0.8	0.7	0.2	0.57	110	0.7	0.8	0.8	0.77	110	0.7	0.2	0.2	0.36
111	0.8	0.7	0.6	0.70	111	0.3	0.8	0.4	0.50	111	0.1	0.4	0.3	0.26
112	0.8	0.7	0.3	0.60	112	0.5	0.8	0.2	0.50	112	0.3	0.9	0.3	0.50
120	0.8	0.4	0.2	0.47	120	0.7	0.1	0.1	0.30	120	0.1	0.2	0.7	0.36
121	0.8	0.4	0.6	0.60	121	0.3	0.1	0.5	0.30	121	0.5	0.3	0.5	0.44
122	0.8	0.4	0.3	0.50	122	0.5	0.1	0.7	0.43	122	0.5	0.4	0.5	0.48
200	0.6	0.5	0.2	0.43	200	0.9	0.4	0.5	0.60	200	0.7	0.8	0.8	0.77
201	0.6	0.5	0.6	0.57	201	0.4	0.4	0.7	0.50	201	0.6	0.9	0.4	0.65
202	0.6	0.5	0.3	0.47	202	0.1	0.4	0.6	0.37	202	0.8	0.7	0.7	0.75
210	0.6	0.7	0.2	0.50	210	0.9	0.2	0.8	0.63	210	0.4	0.2	0.9	0.50
211	0.6	0.7	0.6	0.63	211	0.4	0.2	0.4	0.33	211	0.8	0.9	0.1	0.60
212	0.6	0.7	0.3	0.53	212	0.1	0.2	0.2	0.17	212	0.9	0.1	0.3	0.43
220	0.6	0.4	0.2	0.40	220	0.9	0.7	0.1	0.57	220	0.9	0.1	0.2	0.39
221	0.6	0.4	0.6	0.53	221	0.4	0.7	0.5	0.53	221	0.6	0.0	0.6	0.40
222	0.6	0.4	0.3	0.43	222	0.1	0.7	0.7	0.50	222	0.4	0.8	0.9	0.69

Table 6 Information available to agents with $\mathbf{X_n} = 1 - w_{n,r}$ (starting at 000 in Table 5 landscape with K = 1)

Dimension	X_n	$P_{n,q}$
n1	1—0.6 = 0.4	0.4 / (0.4 + 0.7 + 0.5) = 0.25
n2	1—0.3 = 0.7	0.7 / (0.4 + 0.7 + 0.5) = 0.44
n3	1—0.5 = 0.5	0.5 / (0.4 + 0.7 + 0.5) = 0.31

Table 7 Information available to agents with $\mathbf{X_{n,q}} = w_{n,q} - w_{n,r}$ (starting at 000 in the Table 5 landscape with K = 1)

String	$X_{n,q}$	W	$P_{n,q}$
000	(current)	0.47	-
001	0.7—0.5 = 0.2	0.60	0.2 / (0.2 + 0.1 + 0.2 + 0.6 + 0.1 + 0.3) = 0.13
002	0.6—0.5 = 0.1	0.37	0.1 / (0.2 + 0.1 + 0.2 + 0.6 + 0.1 + 0.3) = 0.07
010	0.5—0.3 = 0.2	0.63	0.2 / (0.2 + 0.1 + 0.2 + 0.6 + 0.1 + 0.3) = 0.13
020	0.9—0.3 = 0.6	0.53	0.6 / (0.2 + 0.1 + 0.2 + 0.6 + 0.1 + 0.3) = 0.40
100	0.7—0.6 = 0.1	0.60	0.1 / (0.2 + 0.1 + 0.2 + 0.6 + 0.1 + 0.3) = 0.07
200	0.9—0.6 = 0.3	0.60	0.3 / (0.2 + 0.1 + 0.2 + 0.6 + 0.1 + 0.3) = 0.20

Data availability Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

Declarations

Ethical conduct Respondents that participated in the survey questionnaire were aware of and agreed with the research purposes of the data collection.

Conflict of interest The authors declare they have no conflict of interests.

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