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When the Recipe Is More Important Than the Ingredients: A Qualitative Comparative Analysis (QCA) of Service Innovation Configurations

Andrea Ordanini[1], A. Parasuraman[2], and Gaia Rubera[1]

Abstract

Service innovation is a primary source of competitive advantage and a research priority. However, empirical evidence about the impact of innovativeness on new service adoption is inconclusive. A plausible explanation is that service innovation has thus far been studied using new product frameworks that do not fully capture the complexity of new service assessments by customers. We propose a different, holistic framework, which posits that new service adoption does not depend on individual service attributes, but on specific configurations of such attributes. We investigate this framework in a luxury hotel service context, using qualitative comparative analysis, a set-membership technique that is new to service research and suitable for configuration analyses. Results confirm that individual service attributes have complex trade-off effects and that only specific combinations of attributes act as sufficient conditions for new service adoption. Moreover, the composition of such combinations differs according to the different coproduction requirements. Our findings contribute to managerial practice by providing new insights for improving the service-development process and the launch strategy for new services. They also augment extant service knowledge by demonstrating why interdependencies among various innovation attributes are important to consider for gaining an accurate understanding of new service adoption.

Keywords

new service, configuration, QCA, service adoption

Service innovation is a primary source of competitive advantage (Lusch, Vargo, and O'Brien 2007) and a research priority in the service field (Ostrom et al. 2010). Despite the importance of service innovation phenomena, and the complexity of new services (Hauser, Tellis, and Griffin 2006), research to date on new service adoption has been guided primarily by simple frameworks borrowed from the new product literature (Menor, Tatikonda, and Sampson 2002). However, findings from such research have been unable to pinpoint the determinants of effective new service adoption. Individual-established drivers of new product adoption (e.g., perceived novelty) have been found to have ambiguous and inconsistent effects in the context of new service adoption (Szymanski, Kroff, and Troy 2007).

Against this backdrop, we propose a different, holistic approach for investigating new service adoption phenomena. Invoking insights from service marketing theory (Murray 1991) and the literature on attribute information processing (Veryzer and Hutchinson 1998), we propose that new service adoption does not depend on *individual* service attributes but on specific *configurations* of attributes—that is, a new service represents a bundle of interlinked attributes, and its value derives from the perceived appeal of the "gestalt" of attribute levels present in the bundle. Drawing on the literature on service design (Bitner 1992; Zomerdijk and Voss 2010) and customer participation (Bendapudi and Leone 2003; Lengnick-Hall 1996), we also posit that *coproduction* requirements influence customers' adoption intentions (Xie, Bagozzi, and Troye 2008). Therefore, new service adoption decisions are informed by not only the bundle of interconnected attributes but also the extent to which the bundle *fits* the coproduction requirements of the context in which the new service is offered. This raises the research question:

> **Research Question:** Which configurations of new service attributes—and coproduction requirements—lead to new service adoption?

We address this question in the context of luxury hotel services using qualitative comparative analysis (hereafter QCA), a

[1] Marketing Department, Bocconi University, Milan, Italy
[2] Department of Marketing, School of Business, University of Miami, Coral Gables, FL, USA

Corresponding Author:
Andrea Ordanini, Marketing Department & Cermes, Bocconi University, 20136 Milan, Italy.
Email: andrea.ordanini@unibocconi.it

set-membership analytical technique appropriate for complex configuration analyses (Ragin 2000). Set theory methods such as QCA assume that the influence of attributes (in our case, new service attributes and coproduction requirements) on a specific outcome (adoption) depends on how the attributes are combined, rather than on the levels of the individual attributes per se. These methods use Boolean algebra rules to identify which of the attribute combinations, if any, act as sufficient or necessary conditions for the outcome (Fiss 2007). Our study's findings confirm that individual service attributes have complex trade-off effects and that only certain *combinations* of attributes act as sufficient conditions for adoption. Moreover, the composition of these combinations differs in terms of coproduction requirements, implying that new service attributes and coproduction requirements have to be properly aligned to elicit adoption intentions. The findings also show that QCA offers richer insights about new service adoption than do conventional techniques such as cluster and regression analyses.

Our study contributes to managerial practice in two ways. First, it introduces a new approach for improving the service-development process. By employing QCA for concept testing, managers can identify early in the process *when* an individual service characteristic increases or reduces consumer appeal, and discover the *alternative* ways in which such characteristics can be combined to increase the likelihood of adoption. This gives managers more than one potentially successful recipe for designing a new service, reducing the risk of either dropping potentially good ideas prematurely, or locking into one seemingly attractive idea that might subsequently fail. Second, our study shows how set-theoretic methods can also improve launch strategies. QCA can be used to develop an informed typology of potential users, showing what makes the service attractive and *to whom*. Based on these results, service managers can customize the launch strategy for different segments of potential users by formulating an appropriate positioning and promotional strategy for each.

In the theoretical realm, our research responds to previous calls to identify new approaches for studying service-innovation phenomena (Hauser, Tellis, and Griffin 2006; Menor, Tatikonda, and Sampson 2002; Ostrom et al. 2010). Our findings emphasize why advancing our understanding of service innovation requires studying "the interdependencies among innovation attributes and how these affect innovation adoption" (Arts, Frambach, and Bijmolt 2011, p. 143). The use of QCA and configuration logic captures the complexities underlying consumers' decisions to adopt new services and identifies the ways in which service attributes and coproduction should be aligned to elicit adoption. The findings also help explain why knowledge to date about the role of individual drivers of service adoption has been inconclusive (Szymanski, Kroff, and Troy 2007).

New Product Adoption

Current knowledge on new service adoption largely derives from research employing a tangible goods logic (Hauser, Tellis, and Griffin 2006; Menor, Tatikonda, and Sampson 2002) and relies on Rogers' (1983) diffusion-of-innovations framework, according to which the attributes of the potential adopter and, more importantly, *the perceived attributes of the innovation*, are the major drivers of adoption (Gatignon and Robertson 1985; Meuter et al. 2005).[1] Such perceived attributes (hereafter referred to as "attributes") can be viewed as components of the so-called market knowledge, that is, the gestalt of information about customer needs and preferences available to managers. Market knowledge is considered important for innovation success because it inspires managers in designing a new offering and assists them in properly communicating its potential value (Danneels 2002). According to extant new product adoption literature (Arts, Frambach, and Bijmolt 2011), three innovation attributes proposed by Rogers' framework are particularly salient in attitude formation during the persuasion stage of the adoption decision process: relative advantage, complexity, and meaningfulness (or compatibility).

Relative advantage reflects the new offering's perceived superiority over other alternatives on dimensions such as quality and function (Gatignon and Robertson 1985). *Complexity* represents the degree to which an innovation is perceived to be difficult to understand or operate and hence the learning effort needed to adopt a new product (Danneels 2002). *Meaningfulness* denotes the degree to which the innovation appears useful and consistent to the potential adopter, and capable of satisfying his or her needs (Cooper and Kleinschmidt 1987). Apart from Rogers' main drivers, the literature has introduced *novelty*, reflecting the perceived degree of incongruence with existing alternatives (Firth and Narayanan 1996) and uncertainty concerning the consequences of adoption (Hoeffler 2003). In short, positive adoption intentions depend on the extent to which *benefits*—relative advantage and meaningfulness—offset *costs*—learning effort and risks associated with complexity and novelty.

New Service Adoption: A Holistic View

A primary tenet of the product adoption literature is that the effects of a new offering's attributes on adoption intentions are *additive*, with each individual trait exerting an independent effect. This tenet assumes that potential adopters disentangle a new offering's elements, assess them separately, and then pool the assessments in deciding whether to adopt (Arts, Frambach, and Bijmolt 2011). According to the attribution information-processing literature (Veryzer and Hutchinson 1998), this assumption is realistic for simple products with "atomistic" properties, but not for complex products having "relational" properties, meaning that their attributes are only perceived in relationship to one another and, therefore, elicit customer reactions that are interactive rather than independent.

While many tangible goods have atomistic properties, services primarily have relational properties. Services are highly interactive and experiential, with their value to customers emerging from a simultaneous integration of actors—providers and customers, processes, and resources (Vargo and Lusch

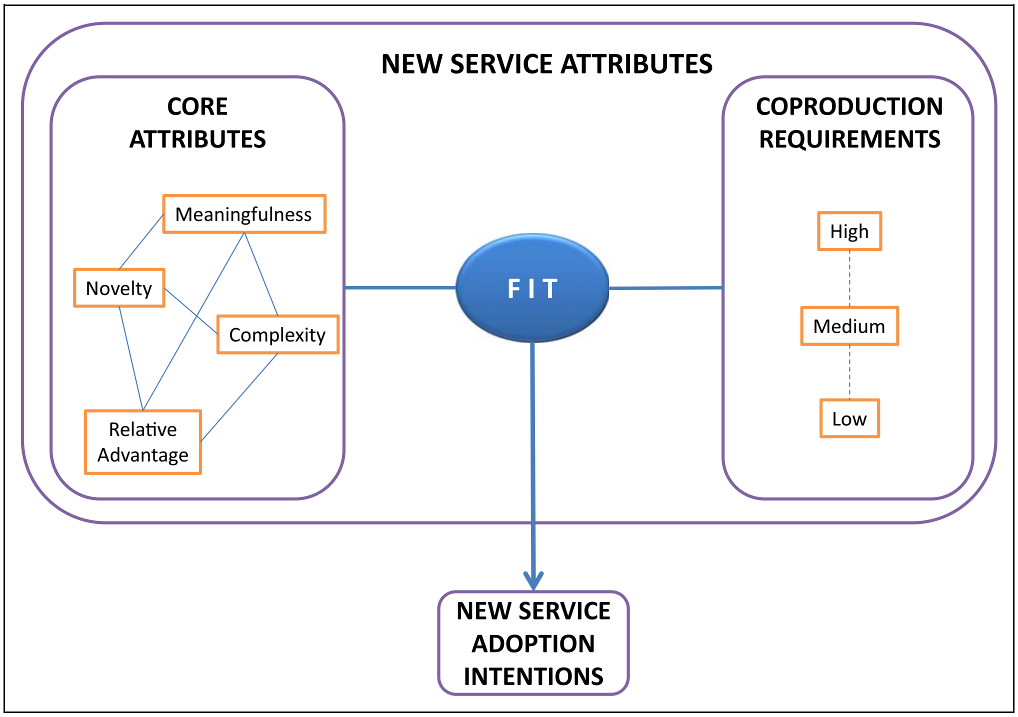

Figure 1. A configuration view of new service adoption.

2008) and being delivered in its entirety at the end of the integration process (Gallouj and Weinstein 1997; Smith, Bolton, and Wagner 1999). Moreover, a customer typically experiences a new service within a complex mix of environmental features, that is, the servicescape. The servicescape literature posits that, although the service offering's attributes are defined independently, they are perceived by customers as a holistic pattern of interdependent stimuli (Bitner 1992).

Beyond the above-described holistic property, services are more heterogeneous and less predictable than products because customers uniquely cocreate the outcome with the service provider each time (Vargo and Lusch 2008). High levels of coproduction have been found to improve service-quality perceptions since customers can observe service aspects such as process fairness, that are normally hidden from their view (Hui et al. 2004; Lengnick-Hall 1996). On the other hand, greater expected coproduction calls for higher self-efficacy to determine "how to [. . .] proceed from ingredients to finished solutions" (Xie, Bagozzi, and Troye 2008, p. 116). Along the same lines, high-coproduction requirements can influence customers' assessments of their responsibility for the service outcome, such that they tend to attribute negative consequences to the provider and positive ones to themselves, a phenomenon known as self-serving bias (Bendapudi and Leone 2003). There are thus multiple, at times opposing, ways in which customers' perceptions of coproduction requirements might interact with their perceptions of a new service offering's core attributes and hence influence their overall assessment. Therefore, apart from evaluating the configuration of a new service's core attributes, customers implicitly assess if there is an appropriate fit between that configuration and the coproduction requirements of the context in which the new service is offered.

A Configuration Model of New Service Adoption

Integrating insights from the literature streams reviewed in the preceding sections, we posit that, although key drivers of new product adoption also matter in new service contexts, new service adoption is a complex, multidimensional phenomenon, in which the configuration of the service attributes is more important than the individual attributes; and, there should be an appropriate fit between the configuration and the coproduction requirements of the context in which the new service is offered. This line of reasoning leads to a conceptual framework (Figure 1) based on fit logic and configuration theory.

The fit logic implies that different elements in a given context are not important intrinsically, but that their role depends on how they are aligned (Venkatraman 1989). When multiple variables are involved, fit becomes a systemic phenomenon and may take the form of *profile deviation* when an a priori criterion (e.g., an "ideal" profile) for evaluating congruence exists; in the absence of an a priori evaluative criterion, fit manifests itself as *gestalts* (Venkatraman 1989). Our framework relies on the "fit as gestalts" logic since, as discussed previously, adoption of service innovations involves the coalignment of multiple variables—in our case, service attributes and coproduction requirements—with no specific form of coalignment available as an a priori benchmark.

Fit-as-gestalts is at the core of configuration theory (Ragin 2000) which focuses on complex, multidimensional phenomena at different levels (firms, groups, individuals) that tend to cluster into archetypes described by common patterns of coherent attributes. As its fundamental premise, configuration theory posits that the same set of causal factors can lead to different outcomes, depending on how such factors are arranged. Three principles underlie configuration theory: Outcomes of interest rarely result from a single causal factor; causal factors rarely operate in isolation; and, the same causal factor may have different—even opposing—effects depending on the context (Greckhamer et al. 2008). Such principles imply the concept of "equifinality," according to which the same outcome can be achieved through different configurations of causal factors (Ragin 2000). While the configurations of factors pertaining to a phenomenon can potentially be numerous, equifinal configurations that effectively explain the phenomenon typically reduce to a few coherent patterns of attributes. The purpose of configuration analysis is to discover those few equifinal configurations.

Our conceptual framework posits that while adoption depends on the four primary service attributes (relative advantage, complexity, meaningfulness, and novelty), only when customers perceive *meaningful configurations* of these attributes that, in turn, *fit with coproduction requirements,* is adoption likely to occur.[2] The general propositions implied in our configurational framework are as follows:

Proposition 1: The same attribute can either foster or inhibit new service adoption, depending on how it is configured with other attributes.

Proposition 2: Disparate configurations of service attributes are equifinal in leading to adoption.

Proposition 3: For adoption to occur, a configuration of attributes must be perceived as fitting the coproduction requirements.

Data Collection and Measures

For our study, we selected a hotel service that had received recognition as the most creative service activity in the luxury hospitality category in a competition among 90 five-star hotels in Italy. The award-winning service involves a "personal guest-experience planner" who is available for a 3-day period to hotel customers choosing a special service package. This person shares various social experiences with the customers, ranging from shopping to thermal baths to sports activities to park visits for children. This service enables people who travel alone, often for business, to complement their visit with a pleasant social experience; it also offers families or small groups unique experiences they may not be able to design by themselves.

We hired a professional telemarketing company to recruit a random sample 300 customers who had stayed at a luxury hotel for leisure during the previous 3 years. Each customer received an e-mailed description of the new service and was scheduled for an interview 3 to 5 days later. Data on the study variables were collected during the interviews. The new service descriptions did not reveal the luxury hotel's name, to avoid potential biases that can be particularly strong for services (Folkes and Patrick 2003). We also conducted detailed interviews with six luxury hotel managers and pretested the measurement instrument with a convenience sample of 15 customers.

We operationalized four of the five adoption drivers in Figure 1 (novelty, meaningfulness, complexity, and relative advantage) and the outcome construct of adoption intentions as perceptual measures. Appendix A contains our construct measures, adapted from existing scales, and their reliability coefficients. We altered the original semantic anchors of the scales to be consistent with conventional set-membership calibration procedures for configuration analysis (Ragin 2000; more on this in the next section).

Coproduction requirements, the fifth adoption driver in Figure 1, reflect an organizational choice made by the service firm (Vargo and Lusch 2008). We therefore manipulated this construct with three descriptive scenarios (shown in Appendix B) corresponding to the types of coproduction in the service literature: firm production, joint production, and customer production (Meuter et al. 2005). We then randomly assigned the 300 study participants to the three coproduction contexts to generate variance in the construct.[3]

QCA

We investigate our configuration framework using QCA (Fiss 2007; Ragin 2000). QCA is a set-theoretic method that empirically examines the relationships between the outcome of interest (adoption intentions in our study) and *all* possible combinations of binary states (i.e., presence or absence) of its predictors (perceived new service attributes and coproduction requirements; Longest and Vaisey 2008). Originally developed for sociology and political science, QCA is a mixed qualitative-quantitative technique that has been gaining attention in management (Fiss 2007; Greckamer, Misangyi, Elms, and Lacey 2008) and innovation (Ordanini and Maglio 2009) research for investigating complex configurations of constructs. QCA performs a systematic cross-case analysis that models relations among variables in terms of *set membership* and uses Boolean algebra to identify configurations that reflect the *necessary* and *sufficient conditions* for an outcome of interest. The application of QCA involves four sequential tasks (Fiss 2011): definition of the property space, development of set-membership measures, evaluation of consistency in set relations, and logical reduction.

The Property Space

QCA starts by defining the property space, which consists of all possible configurations of drivers of an outcome. Since the property space delimits potential explanations of the outcome, the drivers should be chosen carefully and anchored in extant theoretical knowledge. Our study employs important innovation drivers identified by the product-innovation literature and a critical contextual element for innovation in the service literature: coproduction. Accordingly, the property space consists of all combinations of binary states, that is, presence or absence, of the

Table 1. Configurations of Binary States of New Service Adoption Drivers: Distribution of Best-Fit Cases.

Configurations	Cases	%
NOV*MEAN*compl*ADV*COPR	43	15.18
NOV*MEAN*compl*ADV*copr	36	11.88
NOV*MEAN*COMPL*ADV*COPR	28	9.24
NOV*MEAN*COMPL*ADV*copr	12	3.96
NOV*MEAN*COMPL*adv*COPR	4	1.32
NOV*MEAN*COMPL*adv*copr	3	0.99
NOV*mean*compl*ADV*COPR	6	1.98
NOV*mean*compl*ADV*copr	8	2.64
NOV*mean*compl*adv*COPR	6	1.98
NOV*mean*compl*adv*copr	2	0.66
nov*mean*COMPL*ADV*COPR	9	2.97
NOV*mean*COMPL*ADV*copr	6	1.98
nov*mean*COMPL*adv*COPR	13	4.29
Nov*mean*COMPL*adv*copr	6	1.98
nov*MEAN*compl*ADV*COPR	6	1.98
nov*MEAN*compl*ADV*copr	1	0.33
nov*MEAN*COMPL*ADV*COPR	10	3.30
nov*MEAN*COMPL*ADV*copr	3	0.99
nov*MEAN*COMPL*adv*COPR	5	1.65
nov*MEAN*COMPL*adv*copr	1	0.33
nov*mean*compl*ADV*COPR	11	3.63
nov*mean*compl*ADV*copr	1	0.33
nov*mean*compl*adv*COPR	14	4.62
nov*mean*compl*adv*copr	1	0.33
nov*mean*COMPL*ADV*COPR	11	3.63
nov*mean*COMPL*ADV*copr	7	2.31
nov*mean*COMPL*adv*COPR	33	10.89
nov*mean*COMPL*adv*copr	14	4.62
Total	300	100%

Note. Nov = novelty; Mean = meaningfulness; Compl = complexity; Adv = relative advantage; Copr = coproduction. Lowercase = attribute absent, uppercase = attribute present.
For four configurations, empirical evidence is lacking: #NOV*MEAN*compl*adv*COPR#; #NOV*MEAN*compl*adv*copr#; #nov*MEAN*compl*adv*COPR#; and #nov*MEAN*compl*adv*copr#.

four service attributes that could influence adoption (novelty, meaningfulness, relative advantage, and complexity) and the coproduction requirements (i.e., $2^5 = 32$ combinations). The combinations, or configurations, empirically present in our data appear as rows in Table 1, with uppercase letters indicating the presence of an attribute and lowercase letters indicating its absence.

Set-Membership Measures

Since QCA is based on the concept of set membership, the original measures need to be transformed to reflect the extent to which each customer, based on his or her perceptions, can be considered a member of the different sets reflecting configurations of service attributes. While sets are expressed in binary form (presence/absence of attributes), our variables are not naturally dichotomous; so we generate membership measures using a fuzzy-set calibration approach, which allows membership scores to reflect the varying degrees to which different cases belong to a set, ranging from 1 (*full membership in the set*) to 0 (*full nonmembership in the set*), with intermediate membership levels in between (Ragin 2000). Appendix C offers further details about fuzzy-set calibration of our measures. Table 2 shows means, standard deviations, and correlations of the membership scores for all variables included in the analysis.

After generating fuzzy-set measures for individual attributes, including coproduction, by applying Boolean algebra rules it is then possible to build membership scores for configurations (listed in Table 1), which include more than one attribute, with each being either present or absent. Specifically, for each customer, the lowest membership score provides the degree of membership in the configuration. Moreover, the degree of membership in the negation of a set, for example, nonnovel services, is equal to the complement to 1 of the membership score in that set (i.e., one membership in the novel set; Rihoux and Ragin 2009). By applying these rules, each customer will have some degree of fuzzy membership in every configuration of adoption attributes although, by assumption, in only one configuration, called *best-fit case*, will his or her membership measure be greater than 0.5 (Longest and Vaisey 2008). The second column of Table 1 shows the distribution of best-fit cases (customers) across the configurations in our sample.

Consistency in Set Relations

The next task in applying QCA is the assessment of the subset relationships, that is, evaluating which configurations of attributes can act as sufficient conditions for new service adoption. This requires cross-case comparison of memberships between the causal sets (configurations of attributes), denoted as #X#, and the outcome set (the configuration of new service adoption), denoted as #Y#. The proportion of consistent cases—the number of customers who are members of both a causal set and the outcome set, divided by the total number of customers who are members of that causal set—is used to assess the consistency of the subset relationship for any specific causal set. For instance, if all customers who perceive a new service as having the same attribute configuration are also adopters of the service, the consistency score for that configuration will be 1. Appendix D provides an illustration of such a scenario and elaborates on the logic underlying the derivation of necessary and sufficient conditions in QCA.

However, with fuzzy sets, the assessment of consistency is somewhat more complex because customers can have partial memberships in all possible causal sets. According to set theory, a consistent subset relation with fuzzy measures emerges when membership scores in a given causal set of attributes are consistently less than or equal to the membership scores in the outcome set. The consistency measure in this case is thus calculated as the sum of the consistent, or shared, membership scores in a causal set, divided by the sum of all the membership scores that pertain to that causal set:

$$\text{Consistency } (X_i \le Y_i) = \sum_i [\min (X_i;Y_i)] / \sum_i (X_i),$$

Table 2. Means, Standard Deviations, and Pairwise Correlations of Variables (Fuzzy-Set Scores).

	M	*SD*	Adoption	Novelty	Meanness	Complexity	Relative Advantage	Coproduction
Adoption	0.51	0.40	1					
Novelty	0.56	0.36	0.51*	1				
Meaningfulness	0.47	0.37	0.48*	0.51*	1			
Complexity	0.40	0.36	0.41*	0.34*	0.25*	1		
Relative Advantage	0.61	0.38	0.63*	0.51*	0.56*	0.40*	1	
Coproduction	0.55	0.37	−0.31*	−0.27*	−0.21*	−0.02	−0.24*	1

*$p < .05$.

where for customer i, X_i = membership score in the X configuration and Y_i = membership score in the outcome set.

To avoid deterministic solutions, detecting a subset relation does not require that all customers who belong to a configuration also belong to the outcome set (i.e., consistency = 1, as in the illustration in Appendix D). Instead, based on the concept of quasi-sufficiency, for a configuration to be considered as sufficient, its consistency measure should statistically exceed a minimum threshold, so that a "few" inconsistent cases are allowed because of random error (Fiss 2007). In line with QCA literature, we employ a consistency threshold of .75 and use a Wald test to detect statistical significance (Longest and Vaisey 2008). To mitigate the potential effect of measurement and coding errors, only configurations that are represented by a certain minimum number of best-fit cases are normally included in the analysis (Fiss 2011), so that we consider only configurations that have at least three best-fit cases or, in other words, those that at least three customers perceive as characterizing the new service.

Logical Reduction

The final task in applying QCA is to prune the sufficient configurations by eliminating redundant elements. To illustrate, consider two attribute-configuration sets that pass the consistency test: #NOVEL*MEANINGFUL*COMPLEX# and NOVEL*meaningful*COMPLEX#. The final, "reduced" configuration in this case is simply #NOVEL*COMPLEX#, because whether the new service is perceived as meaningful or not is irrelevant for adoption. For each final sufficient configuration, a coverage measure is then calculated. While consistency is a measure of the significance of a subset relationship, coverage is a measure of its relevance and reflects the share of consistent memberships as a proportion of total memberships in the outcome set. Coverage thus enables the assessment of the empirical importance of sufficient configurations. Formally:

$$\text{Coverage } (X_i \leq Y_i) = \sum_i \ [\min \ (X_i; Y_i)] / \sum_i \ (Y_i),$$

where for customer i, X_i = membership score in the X configuration, and Y_i = membership score in the outcome set.

The reduction procedure includes an important step related to the treatment of "remainders," which are configurations with an insufficient number of best-fit cases in the sample due to the lack of empirical data (Ragin and Sonnet 2004). For example, our study lacks empirical instances for 4 of the 32 configurations (see Table 1), meaning that no customers perceived the new service as being represented by these configurations of attributes. Given the relatively small number of remainders (4 of the 32), and consistent with QCA guidelines (Fiss 2011), we excluded them from the analysis.

Table 3. Sufficient Configurations for New Service Adoption.

Sufficient Sets	Raw Coverage	Unique Coverage	Consistency
*mean*compl*ADV*COPR	.20	.06	.82
NOV*ADV*copr	.51	.08	.88
NOV*MEAN*ADV	.63	.17	.87

Note. Nov = novelty; Mean = meaningfulness; Compl = complexity; Adv = relative advantage; Copr = coproduction. Lowercase = attribute absent, uppercase = attribute present.
Total coverage = 0.78. Solution consistency = 0.84.

Findings and Discussion

Table 3 summarizes results from the QCA conducted by using the STATA fuzzy package (Longest and Vaisey 2008). The rows show the configurations of attributes that are sufficient for inducing adoption of the new service, with consistency and coverage measures for each configuration, and for the whole solution.

Three distinct configurations that can all stimulate adoption intentions emerge. First, apart from relative advantage, present in all three configurations, the adoption of the new luxury hotel service can be induced when customers perceive the new service as being noncomplex and involving a high degree of coproduction, even if not addressing immediate or readily apparent needs (first configuration in Table 3). A second configuration conducive to adoption involves the service being perceived as novel but requiring low coproduction effort (second configuration). A final possibility is when the new service is perceived as being both novel and meaningful, irrespective of the amount of coproduction required (third configuration). We now use these findings to examine our three propositions.

Can Individual Service Attributes Foster or Inhibit New Service Adoption? (Proposition 1)

One attribute germane to new service adoption—*relative advantage*—is present in all three sufficient configurations in Table 3. Since the three configurations explain about 78% of the adoption intentions in our sample (total coverage = .78), relative advantage can be viewed as an almost necessary condition for adoption, a sort of hygiene factor, whose absence generally inhibits adoption intentions, but whose sole presence cannot induce adoption. For the other adoption attributes trade-off effects are at work. *Novelty* is present in two of the three sufficient configurations, but is irrelevant in the first sufficient configuration in Table 3. This finding offers a first plausible explanation for the weak link between perceived innovativeness and new service success that Szymanski, Kroff, and Troy (2007) found in their review of previous studies: Novelty influences new service adoption in a contingent fashion—it fosters adoption and hence new service success only when potential adopters perceive other attributes of the new service as being congruent with novelty in a given context. In other cases, adoption can occur irrespective of novelty, or even when novelty is absent, as happens in the first configuration in Table 3. Thus, while perceived novelty may foster adoption in some cases, by itself it is not sufficient for adoption. The absence of *complexity* is required to elicit adoption in the first configuration in Table 3, while it is an indifferent attribute in the other two routes to adoption. This pattern of findings suggests that perceived complexity is probably a less frequent obstacle to adoption than traditionally believed, since its absence only comes into play for one specific route to new service adoption. Complex services can thus be adopted, provided other attributes are perceived as being congruent.

The presence of *meaningfulness* is critical for the third configuration in Table 3, but new service adoption can occur even in the absence of meaningfulness (first configuration), as well as in situations where meaningfulness is irrelevant (second configuration). This is another intriguing result, given the importance accorded to meaningfulness in the new product adoption literature (Szymanski, Kroff, and Troy 2007). The role of meaningfulness is apparently less straightforward for new service adoption because it is contingent on the perceived levels of other attributes. The three sufficient configurations in Table 3 collectively suggest that:

- relative advantage is a necessary but not sufficient condition for adoption;
- novelty, noncomplexity, and meaningfulness are neither necessary nor sufficient for adoption;
- novelty and noncomplexity can be either present or irrelevant for adoption; and
- meaningfulness can be either present, absent, or irrelevant for adoption.

Overall, these findings support Proposition 1—individual attributes, depending on how they are configured with other attributes, may foster or inhibit adoption.

Are There Multiple Routes to New Service Adoption? (Proposition 2)

Table 3 shows three equifinal routes to new service adoption. These routes reflect the different *reasons* or *motivations* for adoption based on how customers holistically perceive the new service. Since QCA findings are "case" and not "variable" based (Ragin 2000), each solution reflects both a combination of variables related to the outcome and the group of subjects associated with that combination. Stated differently, the QCA solutions allow for building an informed typology (Fiss 2011), in which each configuration describes a segment of adopters who perceive the new service as a distinct combination of attributes. The first configuration in Table 3 appeals to customers who do not perceive the new service as being complex or necessarily addressing immediate needs (absence of complexity and meaningfulness), but are attracted to it primarily by the prospect, and perhaps excitement, of being involved in designing and personalizing the service experience (high coproduction). This route corresponds to an adopter segment that could be labeled *participative* in that it apparently trades off the high-coproduction effort against the low learning effort due to low complexity. The notion that customers may show interest in a service that they do not perceive as being immediately useful seems counterintuitive; however, the new product literature suggests that customers may be unable to articulate their needs and that their needs may evolve over time as they learn to use a new product (Dougherty 2001). The service literature also posits that coproduction makes it difficult for customers to predict accurately the usefulness of a new service before experiencing the service (Xie, Bagozzi, and Troye 2008).

The second configuration in Table 3 describes another adoption route, selected by customers who perceive a new service as being novel, and hence perhaps risky, but apparently trade-off that risk against not having to take responsibility (low coproduction) if the service "fails" in some way. This customer segment could be labeled *defensive* because they can attribute any service failure to the provider rather than to themselves. In contrast to the *participative* segment, for which the apparent adoption motivator is the opportunity to get involved in the service process and shape its outcome, the defensive segment seems to be motivated by the sheer novelty of the new service, coupled with low involvement in the service process.

The third configuration in Table 3 implies another adoption route that should appeal to customers who perceive a new service as being novel *and* addressing current needs. Of the three sufficient configurations identified in our study, this configuration achieves the highest level of unique coverage (.17), meaning that it is associated more frequently with adoption intentions than are the other two. The target segment corresponding to this configuration could be labeled *goal oriented* in that perceived ability of the service to address specific customer needs, apart from its being merely novel, is the primary adoption motivator. The service offering's process features—coproduction and adoption complexity—are less relevant to this segment because learning, personalization, and responsibility over the outcome do not affect its choice.

The QCA findings support Proposition 2, given that:

- congruent configurations—and not individual attributes—are what matter in new service adoption; and

- more than one congruent combination of attributes can be equifinal in eliciting adoption.

Is the Fit Between Attribute Configurations and Coproduction Requirements Critical for Adoption? (Proposition 3)

Our findings show that complex trade-off effects—among core service attributes in a configuration, and between the configuration and coproduction requirements—influence adoption. Coproduction is an integral component of the first two of the three sufficient configurations for adoption in Table 3. However, although active customer collaboration is required to stimulate adoption of the first service configuration, the *absence* of customer collaboration is critical for stimulating adoption of the second. Moreover, the level of coproduction is apparently irrelevant for adoption of the third configuration. Thus, ensuring that a new service's core attributes are compatible with the extent of coproduction required is critical for adoption. To illustrate, the first configuration in Table 3 suggests that when a new service requires significant customer involvement in its production, it is advisable to keep its design simple enough (low complexity), and perhaps also somewhat "incomplete" (low meaningfulness) to pique the customer's curiosity and stimulate their active participation. Novelty is not a critical attribute in this configuration, but it is in the second configuration in Table 3, along with low coproduction. This low-coproduction route to adoption fits well with new services that are perceived as extremely innovative (novel, but not necessarily meaningful). This configuration suggests that when a new service offering departs radically from existing alternatives, making prepurchase evaluation of usefulness difficult, it should be designed to minimize customers' involvement (low coproduction), since they may not want to hold themselves responsible for the uncertainty associated with the service. The only route to adoption in which coproduction level apparently does not matter is when customers perceive the new service as novel, meaningful, and possessing relative advantage (third configuration, Table 3). The QCA results[4] largely support our Proposition 3, given that:

- some attribute configurations require specific levels of coproduction to lead to adoption;
- coproduction requirements are irrelevant only if the new service is perceived as being superior on all other attributes.

QCA Versus Conventional Approaches

We performed additional analyses to compare our findings with those obtained through two conventional techniques for analyzing systemic fit in configuration analyses: clustering and deviation score analysis. We also compared the QCA findings with those from an analysis of interaction terms since the latter is used widely in "fit as moderation" contexts (Fiss 2007).

While informative, such comparisons should be made cautiously because, in contrast to conventional approaches, QCA employs distinct assumptions such as complex causality, uses cases instead of variables to establish relations, and addresses different research objectives, namely, identifying configurations that constitute sufficient and necessary conditions for an outcome of interest. Therefore, comparisons from a strict analytical standpoint may not be meaningful; and, we do not claim unconditional superiority for the QCA findings' *empirical validity* over that obtained through other methods. Our goal here is to provide empirical comparisons merely for demonstrating whether and how QCA can help make better sense of the data in research contexts involving attribute configurations.

Clustering Approaches

Consistent with guidelines in Hair et al. (2010), we performed two-step cluster analysis of our data—a hierarchical analysis followed by a *k*-means analysis. Hierarchical clustering using the single-linkage agglomeration method yielded a four-cluster solution. We then used the *k*-means analysis to generate and interpret the profiles of the four clusters (see Appendix E, Table E1). To examine whether cluster membership can predict adoption, we conducted an analysis of variance with the four clusters as treatment levels and adoption intentions as the dependent variable. The results were statistically significant ($F = 62.63$; $p = .000$), with the first two clusters having a strong propensity to adopt (fuzzy score of adoption $> .5$), the third cluster having a strong propensity not to adopt (fuzzy score of adoption $< .5$), and the fourth cluster having a borderline propensity to adopt (fuzzy score of adoption $\cong .5$).

Comparing the cluster analysis results with our QCA results, we first note that cluster membership has weaker explanatory power ($R^2 = .48$ vs. Coverage in QCA $= .78$). Second, only limited insights emerge from the group profiles generated by cluster analysis and related to adoption (Clusters 1 and 2 in Table E1). Both clusters show high levels on all four core attributes, differing only in degree of coproduction; combining these two profiles only yields the third configuration obtained through QCA and reported in Table 3. Thus, cluster analysis does not reveal the complex trade-offs implied by coproduction requirements in the first two configurations detected by QCA (see Table 3). Third, the final cluster in Table E1 seems irrelevant—it describes a profile of attributes that is not significantly related to adoption. Fourth, the remaining identified cluster (Cluster 3) is characterized by high perceived coproduction and low levels of the remaining attributes, and is associated with low adoption intentions. However, a QCA of attribute configurations leading to *nonadoption*[5] revealed *four* distinct configurations that are sufficient for eliciting low adoption intentions. This provides further evidence that the findings from QCA are richer and more precise than those from cluster analysis. We repeated the clustering using latent class analysis, but the results were still inferior to those obtained from QCA (details are available from the authors). To summarize, when applied to our data, cluster analysis does not detect the trade-off effects among novelty, meaningfulness, and complexity, when coproduction is considered. Moreover, it cannot distinguish between necessary and sufficient conditions for adoption, and only captures one of the three configurations for adoption identified by QCA.

Deviation Score Analysis

We next compared our QCA results with those obtained through deviation score analysis (Fiss 2011). In this approach, an "ideal" configuration profile, reflecting the mean profile of a small subset of cases in the sample that are most likely to display the outcome of interest, is first established; next, the deviations of the remaining cases from the ideal profile are examined to see if they are negatively associated with the outcome. We designated customers with average scores higher than 6 on the 3-item adoption-intentions scale as most likely to adopt (this subset constituted 9.6% of our sample). The vector of mean scores for these customers on the five adoption drivers constituted the ideal profile. For the remaining customers, we computed deviation scores as the Euclidean distance of their profiles from the ideal profile (Fiss 2011).[6] We then conducted a regression analysis with deviation and adoption scores as independent and dependent variables, respectively. The results revealed a negative association between the two ($b_{\mathrm{devsc}} = -1.11$; $p = .000$; $R^2 = .34$).

The fuzzy scores on the adoption drivers for the ideal subset of customers indicated a profile high on novelty (.70) and relative advantage (.87); low on coproduction (.35); and indifferent about both meaningfulness (.47) and complexity (.45)—similar to only the second of three QCA-generated configurations in Table 3. Thus, as in the case of cluster analysis, the deviation score analysis has weaker explanatory power vis-à-vis QCA ($R^2 = .34$ vs. coverage $= .78$), and only captures a limited portion of the adoption phenomenon.

Analysis of Interaction Terms

Finally, we conducted regression analysis with adoption intentions as the dependent variable and the five adoption drivers, and their interactions, as independent variables (for comparability with QCA, we used fuzzy scores for all variables; Fiss 2011). The main effects, except for meaningfulness, are statistically significant (see Model 1—Table E2 in Appendix E). Relative advantage is the most important predictor, capturing more than 50% of the explained variance. Novelty shows positive effects, while complexity and coproduction have negative effects; however, in all cases, the effect size is small. These results highlight the limitations of regression analysis in investigating configurational phenomena: While regression parameters imply "average" effects for all variables, QCA shows that relative advantage is necessary but not sufficient for adoption; meaningfulness is not irrelevant as the regression results suggest, but should be low in some instances and high in others to foster adoption, and so on.

Results for Models 2 and 3 in Table E2 show that the sole highest order significant result is for a four-way interaction effect, whose components reflect only the first sufficient configuration in Table 3, characterized by low meaningfulness and complexity, and high coproduction and relative advantage. Thus, analysis of interaction terms only partially captures the complex configuration effects detected through QCA.

Limitations and Robustness Checks

While we believe that set-theoretic methods can contribute significantly to service research, we acknowledge that QCA, as does any research approach, has limitations and involves analytical assumptions that must be considered when interpreting the results. In this section, we address three potential limitations acknowledged in the literature: sensitivity to variables, sensitivity to the sample, and sensitivity to measures (Schneider and Wagemann 2010).

Sensitivity to Variables

Since QCA incorporates various configurations of causal factors, its solution is sensitive to the range of factors included—adding or removing factors could lead to significantly different solutions. While the selection of factors included in our analysis was informed by a comprehensive review of the extant literature on adoption and coproduction, some adoption drivers could have been overlooked. For instance, one potential determinant of adoption intentions not included is the prior relationship of customers with the service firm.[7] We acknowledge this as a limitation and caution that the sufficient configurations of service attributes and coproduction requirements emerging from our findings cannot be generalized to situations beyond those in which customers have no, or similar, prior relationship with the service firm. Future research in this domain might include another manipulation that varies the nature of the customer-firm relationship, such as a long, loyal relationship versus a limited, weak relationship.

To further explore our findings' robustness, we analyzed their sensitivity to three respondent characteristics—gender, age, and customer type (leisure vs. business)—on which we had data. For each of the three sufficient configurations identified by QCA, we evaluated the statistical significance of the difference between the consistency measures for male versus female customers, customers aged less than 45 versus those over 45, and business versus leisure customers. None of the differences were statistically significant, implying that the sufficient configurations are robust across gender, age, and customer type.

Sensitivity to the Sample

Because the set-theoretic approach involves examining all possible combinations of causal factors, each additional factor will exponentially increase the number of potential configurations, necessitating significantly larger samples to reduce the incidence of "remainders," that is, causal configurations with no empirical evidence in the sample data. Thus, a sufficiently large ratio of sample size to number of factors is recommended (Marx 2006). Although the presence of remainders was not a serious issue in our sample (there were only four remainders, which we excluded from the analysis), we performed an additional robustness check. Specifically, we repeated the analysis by imposing a more restrictive minimum threshold of best-fitting cases (five instead of three) to ascertain the sensitivity of our findings to a higher number of remainders. This replication yielded the same three sufficient configurations as did our original analysis, attesting to their stability. Additionally, the composition of the four remainders in our analysis (see note below Table 1) suggests that no customer in our sample perceived the service as being meaningful, noncomplex, and without relative advantage, irrespective of novelty and coproduction. While nothing definitive can be said about the aforementioned attribute configuration's impact, which is a limitation of our study, we can speculate that, given its composition, it is unlikely to significantly affect the adoption process and hence our findings.

Sensitivity to Measures

Another limitation of set-theoretic methods is that they are based on membership measures calibrated around conceptual thresholds (e.g., fully in [a set], more in than out, neither in nor out, more out than in, fully out). The definition of such thresholds and the choice of the calibration mechanism involve the researcher's subjective judgment. Because QCA measures reflect states, not degrees, it is recommended that the criteria for inclusion or exclusion in a set be driven by existing knowledge, to ensure that membership is not simply an empirical question (Ragin 2000). Although our calibration procedure was based on methodological guidelines in the QCA literature (Schneider and Wagemann 2010), we conducted additional checks to verify the robustness of our outcomes across different calibration choices.

First, we changed the threshold levels for inclusion/exclusion in the set by using the scales' extreme points as thresholds (i.e., 1 instead of 2 to be fully out of the set and 7 instead of 6 to be fully in) and redid the analysis. The reanalysis yielded the same results as in Table 3. Next, we changed the cutoff point, originally 4, to 3.5 and 4.5 in separate analyses. The results were consistent across these analyses. We also changed the calibration of the coproduction measures, granting full membership and full nonmembership to the customer-production and firm-production scenarios, respectively. The results were exactly the same as in our original analysis. Finally, we repeated the analysis using a stricter threshold for consistency: 0.8 instead of 0.75. With a consistency target of 0.8, our analysis again yielded two sufficient configurations, equivalent to the second and third original solutions in Table 3.

The collective results from our various reanalyses suggest that the findings are by and large stable and robust.

Managerial Implications

Our QCA findings highlight the importance of coaligning the multiple attributes of a new service, including the extent of coproduction required from customers, for increasing adoption likelihood. For our study's context, the findings suggest that appropriate coalignment of adoption drivers can be achieved through three distinct attribute configurations, corresponding to three different adopter segments—participative, defensive, and goal oriented. The findings also show that service attributes—considered individually—are not particularly informative for predicting adoption intentions because each can either enhance or hamper a new service's appeal to customers, depending on the levels of other attributes. But how can these results—and QCA in general—be actionable by service managers? We offer below practical illustrations to demonstrate their relevance for managerial decision making in two stages of the new service-development process: concept testing and market launch.

Concept testing is the process through which a product or service concept is presented for the first time to consumers to gauge their reactions. It can be used to estimate the concept's potential sales value and/or to modify the concept to enhance its potential value (Kahn 2005). In conventional concept testing, the attributes of the "best" idea to be pursued further are identified through techniques such as focus groups and conjoint analysis, which generates the relative importance of individual attributes. However, given the experiential nature and complexity of services, and because there are trade-offs among individual attributes as our findings reveal, conventional concept tests may be unable to produce a "best" profile that the market also finds attractive. As has been pointed out in the service design literature: "It is unclear.... which service elements create the most compelling contexts and how they can be used to establish customers' emotional connections to a given service" (Zomerdijk and Voss 2010, p. 68). Thus, the "market knowledge" acquired through traditional concept tests may fall short of providing accurate managerial guidance for properly screening and selecting new service ideas.

By employing QCA as an additional tool during concept testing, managers can identify early in the new service-development process *whether* and *under what circumstances* individual attributes will increase—or decrease—the service's appeal to consumers. QCA can also help managers uncover *alternative ways* for combining the attributes in order to induce adoption. For instance, our results suggest that a new hotel service perceived by customers as being low in complexity and meaningfulness is likely to be most appealing when offered in a high-coproduction context requiring extensive customer involvement. A plausible reason for this seemingly counterintuitive insight is that some customers are sufficiently intrigued by the new service to see *potential* value in it, despite its apparent lack of relevance for their *immediate* needs (low meaningfulness); and, more importantly, they are motivated to try the service because of the opportunity to participate actively in shaping the service (high coproduction) and unlocking its potential value without bearing undue effort or risk (low complexity). On the other hand, the same basic service, when perceived as being highly novel but not necessarily meaningful is likely to appeal to customers only when offered in the context of low coproduction. Unique insights such as these illustrate how QCA can offer managers more than one potentially successful recipe for developing a new service, thereby reducing the risk of either prematurely dropping potentially good service concepts—for instance, a service that is perceived as being low on meaningfulness or locking into an apparently "best" service concept that ultimately may not appeal to customers.

Set-theoretic methods such as QCA can also inform managerial decisions during market launch, which is the terminal stage of the new service-development process (Kahn 2005). Correctly identifying the targets for the new service and properly aligning the final offering and related communication strategies to address those targets are critical tasks during market launch. Cluster analysis is traditionally employed for segmentation and positioning purposes at this stage. However, positioning and promoting a new offering for different categories of prospects is more challenging in service contexts than in product contexts because of the highly experiential nature of service outcomes (Xie, Bagozzi, and Troye 2008). As our results show, the same basic service can be perceived differently by—and can appeal for very different reasons to—different categories of potential adopters.

QCA can offer unique insights for improving the effectiveness of launch strategies because it helps managers to develop an informed typology of potential users by uncovering *what* makes a new service attractive and *to whom*. For instance, one of the three prospective customer segments for the hotel service revealed by our QCA findings apparently assumes a "defensive" posture. To market the new service effectively to this segment, promotional communications could stress that customer effort in producing and experiencing this service would be minimal. The "goal-oriented" customer segment revealed by our QCA findings is apparently attracted by the overall superiority of the new service—its high levels of perceived novelty, meaningfulness, and relative advantage—and is indifferent to the degree of coproduction involved. To market effectively to this segment, the new service could be positioned and promoted as an exclusive, high-end service. In short, based on QCA results, service managers can appropriately customize the positioning and promotional aspects of their launch strategies for different segments of prospective customers.

Theoretical and Method Implications

Our study is an inaugural attempt to apply configuration logic and set-theoretic methods, like QCA, in service research and responds to calls in the innovation literature, such as the following one based on a recent meta-analysis: "Future research may therefore focus more on interdependencies among innovation characteristics, and how these affect innovation adoption" (Arts, Frambach, and Bijmolt 2011, p. 25). Our QCA findings confirm that the appeal of a new service indeed depends on the *combined* effects—not the *net* or *additive* effects—of its characteristics.

The findings furthermore suggest that QCA can reveal *which* combinations of characteristics are conducive to new service adoption, thereby unfolding the three main motivations underlying the appeal of the same new service to different prospective customers, and the profiles of the corresponding customer segments. This, in turn, constitutes empirical evidence supporting the conjecture that the effect of innovation characteristics traditionally studied in adoption research is likely to vary among different types of consumers (Arts, Frambach, and Bijmolt 2011).

Our QCA application also helps reconcile the inconclusive evidence concerning the role of individual drivers of service-innovation success (Szymanski, Kroff, and Troy 2007). Our findings suggest that relative advantage, by itself, is necessary—*but not sufficient*—for adoption, while the other three drivers—novelty, meaningfulness, and complexity—when considered individually, are neither necessary nor sufficient. What matters for adoption to occur is whether the drivers and the coproduction setting are appropriately aligned. By establishing that the role of a configuration of service attributes in influencing adoption is contingent on coproduction requirements, our study also extends extant knowledge and clarifies ambiguities concerning the effects of coproduction choices (Bendapudi and Leone 2003). Our QCA results do not mean that individual characteristics are *irrelevant* for new service adoption; on the contrary, they do play a significant role but, individually, they—the "ingredients"—are meaningful only within proper configurations—the "recipes."

Our QCA application also makes a broader methodological contribution to service research in general. QCA is considered to be an "inherently mixed" technique (Teddlie and Tashakkori 2009, p. 273), because it combines within one analysis qualitative inductive reasoning, since data are analyzed "by case" and not "by variable" (Ragin 2000), and quantitative empirical testing, since sufficient and necessary conditions can be derived through statistical methods (Longest and Vaisey 2008). For analyzing phenomena characterized by complex and interlinked questions, the use of such mixed-method techniques is beneficial, because the plurality of perspectives embedded in them leads to more robust and interesting findings (Venkatesh, Brown, and Bala 2013). The use of mixed-method techniques such as QCA is still at its infancy in most business domains. This, coupled with the inherent complexity of many service phenomena, offers service scholars a unique opportunity to stimulate more widespread use of this potentially powerful technique.

Conclusion and Directions for Future Research

To the best of our knowledge, this article is the first to introduce QCA into the service domain and use it to investigate how customers' perceptions of new service attributes influence adoption intentions. The set-theoretic approach and QCA employed herein offer two critical insights not likely to emerge from conventional approaches for studying innovation adoption. First, the same new service attribute can strengthen or weaken adoption intentions depending on the levels of other attributes (including the extent of customer coproduction required); adoption likelihood depends on the collective influence of the attribute *configuration*, not on a simple summation of each attribute's influence. Second, several alternative attribute configurations capable of inducing adoption may exist, rather than one "best" configuration. Specific QCA findings can offer useful practical guidance in the concept-testing and market-launch stages of new service development. Our study offers empirical confirmation for conjectures in the innovation literature based on the complexities associated with customer assessments of new services (vis-à-vis goods). It also helps reconcile some of the inconclusive evidence to date relating to the determinants of new service success. Finally, our study's findings unfold several potentially fruitful research avenues as outlined subsequently.

That QCA offers significant new insights over those obtained from conventional approaches should encourage its use in research on other service topics, both within and outside the service-innovation domain. For instance, within the innovation realm, because our study was conducted in the context of luxury hotels, a high-touch context, the generalizability of the specific configurations for adoption we detected should be verified in other service contexts. Especially insightful would be research that employs QCA in high-tech service contexts to see if sufficient and necessary conditions for adoption are similar to or different from those detected in the present high-touch context.

Outside the innovation realm, QCA can be applied to analyze other complex service phenomena, characterized by trade-offs among multiple factors. For instance, it would be instructive to use set-theoretic methods to investigate the complex trade-offs among various service quality and service productivity facets, which researchers have only recently started exploring empirically (Rust and Huang 2012). Such investigations can offer important insights about, for instance, different combinations of productivity and quality factors, that is, the multiple routes that may lead to service success.

Moreover, given QCA's capability to identify and distinguish between sufficient and necessary configurations for achieving a desired outcome, it could also be used to complement traditional trade-off analysis techniques such as conjoint analysis, by relaxing the strong—and often unrealistic—assumption of independence of the effects of individual service attributes.

Appendix A

Measurement Items

Please rate your perceptions about the described service, according to the following scale:

1	2	3	4	5	6	7
Absolutely no	No	Probably no	Maybe	Probably yes	Yes	Absolutely yes

Note. Novelty (adapted from Im and Workman 2004; $\alpha = .93$)

n1—it is really out of the ordinary.

n2—it can be considered as revolutionary.

n3—it is conventional.[a]

n4—it shows radical differences from other services.

n5—it is in line with other services.[a]

Meaningfulness (adapted from Im and Workman 2004; $\alpha = .94$)

m1—it is relevant to my needs and expectations.

m2—it seems to be unsuitable for my desires.[a]

m3—it is appropriate for my needs and expectations.

m4—it is useful for me.

Complexity (adapted from Calantone, Chan, and Cui 2006; $\alpha = .89$)

c1—it requires little change in customer behavior.[a]

c2—it requires high learning on the part of customers.

c3—it requires little change for customers' use of the service.[a]

Relative advantage (adapted from Calantone, Chan, and Cui 2006; $\alpha = .90$)

r1—it has an outcome quality superior to competitors' services.

r2—it has more visible benefits than competitors' services.

Adoption intentions (adapted from Cameron and James 1987; $\alpha = .94$)

a1—I would positively consider a hotel providing such a service in my choice set.

a2—I would not pay extra for having this service.[a]

a3—I would prefer a hotel offering such a service.

[a]Reverse-scored items.

Appendix B

Coproduction Scenarios

General Description. The *personal guest-experience planner* is a new service being offered to our most important customers. This person will be available to you for 3 days, to create for you with charm and professionalism any of various social experiences you prefer—shopping, sports, visits to attractions, personal care. This service is designed for people who travel alone, often for business, to complement their visit with a pleasant social experience, and for families or small groups that wish to experience something new and exciting that they would be unable to arrange by themselves.

Firm Production Scenario. Please let us know your needs and preferences during your stay in the space below, and we will create the best personalized guest-experience service for you.

Joint Production Scenario. Please let us know your needs and preferences during your stay in the space below. Our professionals will contact you in a few days to set up an appointment of half an hour or so to discuss your needs and preferences in greater

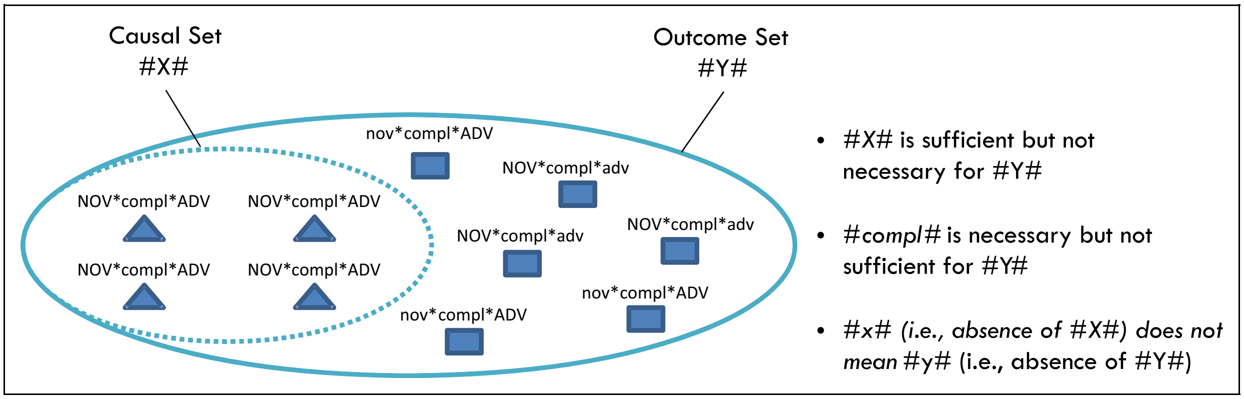

Figure D1. An example of necessary and sufficient conditions. *Note.* * = logical and upper/lower case = presence/absence of an element in the set.

detail. One week before your arrival you will receive an e-mail with a detailed plan of the service. You can either confirm the plan or propose and discuss further changes until 3 days before your arrival.

Customer Production Scenario. Please let us know your needs and preferences during your stay in the space below. After few days, you will receive appropriate materials (e.g., brochures, videos, presentations, etc.) based on your inputs. The material will also contain a detailed list of all the possible activities that you can include in your service package. You can work to personalize your service package until 1 week before your arrival. By that date you will be asked to provide us with all the necessary information to prepare your service package. You can provide this information through our hotel's website or a form that can be printed and faxed. The information necessary to prepare your service package includes: your preferred duration of the entire service package; composition of the package in terms of broad activities; scheduling of the activities during your stay; and, specific services you would like us to include within each broad activity.

Appendix C

Details on the Fuzzy-Set Calibration Procedure

To generate fuzzy set-membership measures for our variables, we first specified three qualitative anchors for our calibration approach: the threshold for full membership in the set, fixed at the rating of 6 ("yes") in our original 7-point scales; the threshold for full nonmembership, fixed at the rating of 2 ("no"); and the indifference point, fixed at the rating of 4 ("maybe").

Once these anchors were set up, all the original values were centered on the cross-over point and transformed to odds ratios (degree of membership/[1 − degree of membership]). Taking the natural logarithm of these odds ratios leads to the desired fuzzy membership measure between 0 and 1 (Longest and Vaisey 2008; Ragin 2000).

For coproduction, which was a manipulated rather than measured construct, customers exposed to the firm production scenario were assigned a fuzzy membership value of .33 (i.e., more out of than in the coproduction set), whereas those exposed to the customer production scenario were assigned a membership value of 1 (fully in the set), and those in the joint production scenario were assigned a membership value of .66 (more in than out). The reason is that, for services, a certain degree of coproduction is always present (Vargo and Lusch 2008); so we used a calibration that does not entail full nonmembership. The cross-over point remains fixed at .5.

Appendix D

The QCA Logic of Sufficiency and Necessity

The illustration in the figure below and the explanation that follows clarify the QCA logic that underlies the derivation of sufficient and necessary conditions for an outcome of interest.

Suppose that four customers perceive a new service as having the same combination of attributes—say, novelty, noncomplexity, and relative advantage. In set-membership terms, these customers (identified by triangles) are defined as *members* of that configuration of perceived attributes, labeled as #X#. Now suppose that these four customers exhibit strong adoption intentions, so that they are also members of the new service adoption set, labeled as #Y#. When members of a causal set (i.e., #X#) are also consistently members of the outcome set (i.e., #Y#), the former configuration of attributes is a logical subset of the outcome set; in other words, #X# is a *sufficient condition* for #Y# (Ragin 2000).

Now consider six other customers (shown as rectangles) who also exhibit strong adoption intentions, but perceive the new service as being characterized by configurational patterns that are different from the pattern perceived by the customers in set #X#. In set-membership terms, these six customers belong to #Y# but not to #X#. In this case, while #X# is a sure path to the outcome (in that all customers perceiving the new service as having the same configuration of features as in #X# are likely to adopt it), other configurations of attributes could also lead to the same likelihood of adoption; therefore, #X# is *sufficient but not necessary* for #Y#. At the same time, as Figure D1 shows, all 10 customers perceive the new service as noncomplex since #compl# (i.e., "absence of complexity" in set-theory nomenclature) appears in all configurations leading to adoption. When *all* occurrences of an outcome (i.e., #Y#) are preceded by the same causal condition (i.e., #compl#), that condition is a logical superset of the outcome, meaning that #compl# is *necessary but not sufficient* for #Y#—the condition alone does not lead to the outcome because adoption depends on combinations of attributes (such as those in #X#), but in its absence the outcome cannot be achieved.

By distinguishing between necessary and sufficient conditions, QCA implies asymmetric relations: If #X# is a sufficient but not necessary condition for #Y#, it follows that absence of #X# does not necessarily lead to the absence of #Y# (Ragin 2000). In fact, in Figure D1, configurations other than #X# also support adoption (i.e., those related to customers represented by rectangles). In contrast to correlational models, in which negative instances of an outcome are mirror images of positive instances (i.e., they involve the same antecedents but with opposite signs), in QCA the absence of an outcome (e.g., non-adoption) has to be investigated separately from its presence (e.g., adoption), since the former will have its own sufficient configurations.

Appendix E

Results From Further Analyses

Table E1. Cluster Analysis ($k = 4$) and ANOVA on Adoption Intentions.[a]

Clusters	Nov	Mean	Compl	Adv	Copr	Ado
1	0.91	0.67	0.58	0.91	0.05	0.79
2	0.73	0.78	0.51	0.87	0.74	0.67
3	0.27	0.15	0.30	0.30	0.87	0.22
4	0.30	0.28	0.14	0.33	0.05	0.43
Centroid	0.56	0.48	0.41	0.61	0.55	0.51

Note. ANOVA = analysis of variance; Nov = novelty; Mean = meaningfulness; Compl = complexity; Adv = relative advantage; Copr = coproduction; Ado = adoption intentions.
[a]Fuzzy membership scores.
F(ANOVA) = 62.63; p = .000.
R^2(ANOVA) = .48.

Table E2. Tobit Regression on New Service Adoption, With Interaction Terms.[a]

	Model 1			Model 2			Model 3		
	Coefficient	*SE*	*p*	Coefficient	*SE*	*p*	Coefficient	*SE*	*p*
_cons	0. 05	0.06	.36						
Nov	0.20	0.06	.00*						
Mean	0.07	0.06	.24						
Compl	−0.20	0.06	.00*						
Adv	0.50	0.07	.00*						
Copr	−0.18	0.05	.00*						
Nov*Mean*Copr				2.00	0.44	.00*			
Mean*Compl*Adv				2.34	0.60	.00*			
Mean*Adv*Copr				0.92	0.47	.05^			
Mean*Compl*Adv*Copr							2.96	1.72	.09^

Note. Nov = novelty; Mean = meaningfulness; Compl = complexity; Adv = relative advantage; Copr = coproduction.
Pseudo R^2 = .76; $\chi^2_{(23)}$ = 316.20; σ = 0.26.
[a]Only significant interactions are reported.
*p < .05. ^p < .1.

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Notes

1. We use the term "attributes" to describe the characteristics of a service innovation "in the eyes of the consumer," which is consistent with how they are conceptualized in the innovation-adoption literature (Arts, Frambach, and Bijmolt 2011).
2. Consistent with previous literature, we first offer general propositions drawn from configuration theory, and then use an appropriate

set-theoretic method, such as qualitative comparative analysis (QCA), to empirically identify the specific configurations associated with adoption intentions (Fiss 2011; Longest and Vaisey 2008).
3. We conducted manipulation checks by asking respondents to rate the amount of resources (time/effort/information) customers would need to expend to use the service. The mean scores indicated significant differences across the three scenarios (details are available from the authors).
4. To assess the results' robustness, we replicated qualitative comparative analysis (QCA) across coproduction states (high vs. low), including only the four innovation attributes in each analysis. The sufficient configurations obtained with this replication are consistent with the original results.
5. QCA findings pertaining to nonadoption are available from the authors.
6. Euclidean distance $= (\Sigma_j\ (X_{sj} - X_{ij})^2)^{1/2}$, where X_{sj} = the sample customer's score on the jth dimension; X_{ij} = the mean score on the jth dimension for the ideal profile; and $j = 1, 2, \ldots, 5$.
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References

Arts, Joep W. C., Ruud T. Frambach, and Tammo H. A. Bijmolt (2011), "Generalizations on Consumer Innovation Adoption: A Meta-analysis on the Drivers of Intention and Behavior," *International Journal of Research in Marketing*, 28 (2), 134-144.

Bendapudi, Neeli and Robert Leone (2003), "Psychological Implications of Customer Participation in Coproduction," *Journal of Marketing*, 67 (1), 14-28.

Bitner, Mary Jo (1992), "Servicescapes: The Impact of Physical Surroundings on Customers and Employees," *Journal of Marketing*, 56 (2), 57-71.

Calantone, Roger, Kwong Chan, and Anna S. Cui (2006), "Decomposing Product Innovativeness and Its Effects upon New Product Success," *Journal of Product Innovation Management*, 23 (5), 408-421.

Cameron, Trudi Ann and Michelle D. James (1987), "Estimating Willingness to Pay from Survey Data: An Alternative Pre-test-market Evaluation Procedure," *Journal of Marketing Research*, 24 (4), 389-395.

Cooper, Robert G. and Elko J. Kleinschmidt (1987), "New Products: What Separates Winners from Losers?," *Journal of Product Innovation Management*, 4 (3), 169-184.

Danneels, Erwin (2002), "The Dynamics of Product Innovation and Firm Competences," *Strategic Management Journal*, 23 (12), 1095-1121.

Dougherty, Deborah (2001), "Reimagining the Differentiation and Integration of Work for Sustained Product Innovation," *Organization Science*, 12 (5), 612-621.

Firth, Richard W. and V. K. Narayanan (1996), "New Product Strategies of Large, Dominant Product Firms: An Exploratory Analysis," *Journal of Product Innovation Management*, 13 (4), 334-347.

Fiss, Peer C. (2011), "Building Better Causal Theories: A Fuzzy Set Approach to Typologies in Organization Research," *Academy of Management Journal*, 54 (2), 393-420.

Fiss, Peer C. (2007), "A Set-theoretic Approach to Organizational Configurations," *Academy of Management Review*, 32 (4), 1180-1198.

Folkes, Valerie S. and Vanessa M. Patrick (2003), "The Positivity Effect in Perceptions of Services: Seen One, Seen Them All?," *Journal of Consumer Research*, 30 (1), 125-137.

Gallouj, Faiz and Olivier Weinstein (1997), "Innovation in Services," *Research Policy*, 26 (4-5), 537-556.

Gatignon, Hubert and Thomas S. Robertson (1985), "A Propositional Inventory for New Diffusion Research," *Journal of Consumer Research*, 11 (4), 849-867.

Greckhamer, Thomas, Vilmos F. Misangyi, Heather Elms, and Rodney Lacey (2008), "Using QCA in Strategic Management Research: An Examination of Combinations of Industry, Corporate, and Business Unit Effects," *Organizational Research Methods*, 11 (4), 695-726.

Hair, Joseph F., William C. Black, Barry J. Babin, and Rolph E. Anderson (2010), *Multivariate Data Analysis* (Global ed.). Englewood Cliffs, NJ: Prentice Hall.

Hauser, John R., Gerry J. Tellis, and Abbie Griffin (2006), "Research on Innovation: A Review and Agenda for Marketing Science," *Marketing Science*, 25 (6), 687-717.

Hoeffler, Steve (2003), "Measuring Preferences for Really New Products," *Journal of Marketing Research*, 60 (4), 406-420.

Hui, Michael K., Xiande Zhao, Xiucheng Fan, and Kevin Au (2004), "When Does the Service Process Matter? A Test of Two Competing Theories," *Journal of Consumer Research*, 31 (4), 465-475.

Im, Subim and John Workman (2004), "The Impact of Creativity on New Product Success," *Journal of Marketing*, 68 (2), 114-132.

Kahn, Kenneth B. (2005), *The PDMA Handbook of New Product Development*, 2nd ed. Hoboken, NJ: John Wiley.

Lengnick-Hall, Cynthia A. (1996), "Customer Contributions to Quality: A Different View of the Customer-oriented Firm," *Academy of Management Review*, 21 (3), 791-824.

Longest, Kyle and Stephen Vaisey (2008), "Fuzzy: A Program for Performing Qualitative Comparative Analyses (QCA) in STATA, " *The STATA Journal*, 8 (1), 79-104.

Lusch, Robert F., Steve L. Vargo, and Matthew O'Brien (2007), "Competing through Service: Insights from Service Dominant Logic," *Journal of Retailing*, 83 (1), 5-18.

Marx, Axel (2006), "Towards More Robust Model Specification in QCA: Results from a Methodological Experiment," COMPASS Working Paper 2006-43, Louvain (Bel).

Menor, Larry J., Mohan V. Tatikonda, and Scott E. Sampson (2002), "New Service Development: Areas for Exploitation and Exploration," *Journal of Operations Management*, 20 (2), 135-157.

Meuter, Matthew L., Mary Jo Bitner, Amy L. Ostrom, and Stephen W. Brown (2005), "Choosing among Alternative Service Delivery Modes: An Investigation of Customer Trial of Self-service Technologies," *Journal of Marketing*, 69 (2), 61-83.

Murray, Keith B. (1991), "A Test of Services Marketing Theory: Consumer Information Acquisition Activities," *Journal of Marketing*, 55 (1), 10-25.

Ordanini, Andrea and Paul P. Maglio (2009), "Market Orientation, Internal Process, and External Network: A Qualitative Comparative Analysis of Decisional Alternatives in New Service Development," *Decision Science*, 40 (3), 601-625.

Ostrom, Amy L., Mary Jo Bitner, Stephen W. Brown, Kevin A. Burkhard, Michael Goul, Vicky Smith-Daniels, Haluk Demirkan, and Elliott Rabinovich (2010), "Moving Forward and Making a Difference: Research Priorities for the Science of Service," *Journal of Service Research*, 13 (1), 4-36.

Ragin, Charles C. and John Sonnett (2004), "Between Complexity and Parsimony: Limited Diversity, Counterfactual Cases, and Comparative Analysis" Working Papers 20-23. COMPASSS, Louvain (Bel).

Ragin, Charles C. (2000), *Fuzzy-set Social Science*. Chicago, IL: University of Chicago Press.

Rihoux, Benoit and Charles C. Ragin (2009), *Configurational Comparative Methods*. Thousand Oaks, CA: Sage.

Rogers, Everett M. (1983), *Diffusion of Innovations*. New York, NY: The Free Press.

Rust, Roland T. and Ming-Hui Huang (2012), "Optimizing Service Productivity," *Journal of Marketing*, 76 (2), 47-66.

Schneider, Carsten Q. and Claudius Wagemann (2010), "Standards of Good Practice in Qualitative Comparative Analysis (QCA) and Fuzzy Sets," *Comparative Sociology*, 9 (3), 397-418.

Smith, Amy K., Ruth N. Bolton, and Janet Wagner (1999), "A Model of Customer Satisfaction with Service Encounters Involving Failure and Recovery," *Journal of Marketing Research*, 36 (3), 356-372.

Szymanski, David M., Michael W. Kroff, and Lisa C. Troy (2007), "Innovativeness and New Product Success: Insights from the Cumulative Evidence," *Journal of the Academy of Marketing Science*, 35 (1), 35-52.

Teddlie, Charles and Abbas Tashakkori (2009), *Foundations of Mixed Methods Research*. Thousand Oaks, CA: Sage.

Vargo, Steve L. and Robert F. Lusch (2008), "Service-dominant Logic: Continuing the Evolution," *Journal of the Academy of Marketing Science*, 36 (1), 1-10.

Viswanath, Venkatesh, Sue A. Brown, and Hillol Bala (2013), "Bridging the Qualitative–Quantitative Divide: Guidelines for Conducting Mixed Methods Research in Information Systems," *MIS Quarterly*, 37 (1), 21-54.

Venkatraman, N. (1989), "The Concept of fit in Strategy Research: Toward Verbal and Statistical Correspondence," *Academy of Management Review*, 14 (3), 423-444.

Veryzer, Robert W. and J. Wesley Hutchinson (1998), "The Influence of Unity and Prototypicality on Aesthetic Responses to New Product Designs," *Journal of Consumer Research*, 24 (4), 374-394.

Xie, Chunyan, Richard P. Bagozzi, and Sigurd V. Troye (2008), "Trying to Prosume: Toward a Theory of Consumers as Cocreators of Value," *Journal of the Academy of Marketing Science*, 36 (1), 109-122.

Zomerdijk, Leonieke and Chris A. Voss (2010), "Service Design for Experience-centric Services," *Journal of Service Research*, 13 (1), 67-82.

Author Biographies

Andrea Ordanini is a Full Professor and the Chairperson of the Marketing Department at Bocconi University. He runs the Service Lab in the Center for Research of Marketing and Services at the same university. His research interests include service marketing, service innovation, and new methods for quantitative analysis.

A. Parasuraman is Professor & Holder of the James W. McLamore Chair, Department of Marketing, University of Miami, School of Business. His research interests concern defining, measuring and leveraging service quality, and investigating the role of technology in service delivery.

Gaia Rubera is an Associate Professor of Marketing at Bocconi University. Prior she was as an Assistant Professor in the Marketing Department at Michigan State University. Her research interests include new product development and service marketing.