Abstract

The impact of big data on innovation is not only driven by technology and analytics. It involves a transformation of the organizational culture, structures, processes, roles and capabilities that underpin the innovation process. Understanding these factors is particularly important for service innovators, given the strong interdependence between the organizational context and technology in service companies. Moreover, in many of these organizations, the innovation process is still deeply rooted in a non-digital past. This study answers the call to understand what are the key characteristics of a systematic process for service innovation in data-rich environments. In particular, we investigate the primary factors that enable existing service organizations to capture the innovation potential inherent in data-rich environments. To this aim, we follow a two-step research design. First, we integrate the service innovation and information systems literatures in a unified conceptual framework that articulates the relationship between data-rich environments and service innovation from an organizational perspective. Second, we carry out 40 semi-structured interviews in seven large service firms, which allow us to refine and populate our initial framework with typologies, concepts, and examples from the field. A major contribution of this study is to articulate the concept of data density, as three distinct processes (pattern spotting, real-time decisioning and synergistic exploration) connecting data-rich environments with service innovation opportunities. We then contribute to a better understanding of technological enablers of innovation in data-rich environments. Finally, we identify a set of organizational enablers that facilitate the links between technology, data density processes, and service innovation. Our findings offer a roadmap for service managers who need to align the service innovation process of their organizations with the opportunities offered by data-rich environments.

Keywords: *service innovation; big data; data-rich environments; data density processes; technological enablers; organizational enablers; qualitative research*

Practitioner points

1. To generate service innovation opportunities from big data, managers of incumbent service firms have to focus their efforts not only on data management and analytics technologies but also on a number of organizational enablers.
2. The data density processes of pattern spotting, real-time decisioning and synergistic exploration make data-driven insights actionable, and mobilize the innovation potential of big data.
3. To make data density processes more effective, companies must promote a customer-centric, data-oriented culture and ensure strong senior management support.
4. Marketing-IT integration and a hub-and-spoke structure of the data-science unit facilitate the emergence of service innovations from big data.
5. Other organizational enablers of service innovation in data-rich environments include working practices (agile processes, recombination, and experimentation), and marketing capabilities (customer education and customer stewardship).

Introduction

Big data are making major inroads into the life of individuals, businesses and society (George, Haas, and Pentland, 2014; Mayer-Schönberger and Cukier, 2013; McAfee et al., 2012). In various services contexts, new entrants such as Uber, Netflix, Spotify, and Deliveroo have launched innovative services that have redefined their industries by leveraging big data technologies. While these success stories are exemplary, on the flipside, a much larger number of incumbent service firms struggle to reconfigure their innovation activities in light of the significant changes brought about by data-rich environments (e.g., D'Emidio et al., 2015). In fact, the fast and sweeping changes in data technologies clash with the legacy of structures, cultures, roles, processes and skills that characterize established service organizations (Davenport, 2014).

Extant literature (e.g. Drejer, 2004; Gallouj and Weinstein, 1997; Menor, Tatikonda, and Sampson, 2002) articulates the differences between service innovation and product innovation, underlining that intangibility, co-production with customers, simultaneity, heterogeneity and perishability are specific characteristics of services that influence their innovation process. These characteristics make the interdependence between the organizational context and technology stronger in service innovation compared to product innovation settings (Nijssen et al., 2006). Given that "services are essentially a series of interactions between participants, processes and physical elements" (Menor, Tatikonda, and Sampson, 2002: 138), data-rich environments are likely to have a differential impact on service innovation compared to product innovation because of the specific interaction of big data technologies with organizational factors in service contexts (Lam et al., 2016). However, still under-theorized is the issue of how existing service organizations need to adapt to capture the innovation potential inherent in data-rich environments. This discussion is still largely practice-driven (e.g., Court, 2015; Mayhew, Saleh, and Williams, 2016), and some authors even question the relationship between big data and innovation (Chai and Shih, 2016; Ross, Beath, and Quaadgras, 2013).

In fact, extant service innovation literature identifies the key dimensions and enablers of service innovation in traditional environments (e.g. Den Hertog, 2000; Fitzsimmons and Fitzsimmons, 2000; Storey at al. 2016). However, this body of literature has not revisited its conceptual building blocks in the context of data-rich environments, and a bias towards cross-sectional and correlational studies hinders the ability to capture transformational processes (Storey et al., 2016). With this theoretical lacuna also comes the issue of managerial relevance. While reflecting on the cumulative field of new service development (NSD) research, Biemans, Griffin and Moenaert (2016, p. 395) recently noted that: “Managers who want to start or improve their service offerings will find only limited help from the available NSD literature”. These gaps in service innovation research are certainly compounded in the context of data-rich environments.

Outside the innovation literature, Information Systems research has documented the transformational impact of information technology on organizational design, decision-making and performance (Huber, 1990; Markus and Robey, 1988; Tippins and Sohi, 2003). More recent studies have focused on the effect of big data on firms’ technological assets and capabilities (e.g., Agarwal and Dhar, 2014; Gandomi and Haider, 2015; Goes, 2014). Some scholars in this domain suggested the need for new theoretical frameworks explaining how big data translate into business value (e.g., Chen, Chiang, and Storey, 2012; Lycett, 2013; Sharma, Mithas, and Kankanhalli, 2014). Yet, this work remains largely conceptual, and tends to adopt a general definition of value/organizational performance that cannot be automatically transferred to a service innovation framework[i].

Against this backdrop, the aim of this study is to integrate the service innovation and information systems literature into a unified conceptual framework that articulates the relationship between data-rich environments and service innovation in incumbent service firms. This study tackles the theoretical and practical gaps in this area, as outlined above, by addressing the following research questions: 1) *What are the processes through which data-rich environments affect service innovation?;* and 2) *What are the factors that enable these processes?* Our main contribution is to develop a conceptual model of the link between data-rich environments and service innovation in incumbent firms that sheds light on intermediate processes and contextual organizational factors. Within this framework, this study proposes a typology of new processes, labeled 'data density' processes (Normann, 2001), which connect data management and analytics technologies to service innovation. In addition, our findings identify the organizational enablers that facilitate the emergence and effectiveness of data density processes. Overall, our study advances the theoretical understanding of the key characteristics of a systematic process for service innovation in data-rich environments, through an investigation of the primary factors that enable existing service organizations to capture the innovation potential inherent in data-rich environments.

From a methodological standpoint, our study responds to recent calls for more fine-grained qualitative approaches to generate in-depth insight into service innovation in new research contexts (Biemans, Griffin and Moenaert, 2016). This complements extant service innovation research (mostly correlational), and information systems studies on big data and value (mainly conceptual). Our research adopted a middle ground between qualitative approaches where the model emerges entirely from the field, and confirmatory-oriented ones that seek to test or corroborate theories and explanations. As delineated by Miles and Huberman (1994, p.17), between these two extremes: "The researcher has an idea of the parts of the phenomenon that are not well understood and knows where to look for these things – in which settings, among which actors…At the outset, then, we have at least a rudimentary conceptual framework, a set of general research questions, and some initial data gathering devices". Therefore, the first step in our research design is to build on existing research frameworks of service innovation and data-rich environments, and integrate their key conceptual blocks, or 'intellectual bins', in a rudimentary model that specifies relationships among them (Miles and Huberman, 1994). Guided by our model and research questions, we then carry out 40 semi-structured interviews in seven large service firms (Rubin and Rubin, 2012). These interviews allowed us to refine and populate our initial framework with typologies, concepts, and examples from the field.

Conceptual Framework

Service Innovation

Fitzsimmons and Fitzsimmons (2000, p.2) define service innovation as "an offering not previously available to customers that results from the addition of offerings, radical changes in the service delivery process, or incremental improvements to existing service packages or delivery processes that customers perceive as being new". According to Storey et al. (2016, p.527), service innovation is "the development of new or enhanced intangible offerings that involves the firm's performance of a task/activity intended to benefit customers". In line with these studies, our work retains the distinction between tangible products and services (Biemans, Griffin and Moenaert, 2016), and refers to service innovation as new or enhanced intangible offerings, and/or new or enhanced ways to deliver them. This choice is in line with the 'demarcation approach' (e.g., Drejer, 2004), which describes innovation models for services as structurally different from those for tangible goods. Barret et al. (2015), Den Hertog (2000), Miles (2008), and Wooder and Baker (2012) among others, organize the conceptual framework of service innovation around three key dimensions: service concept, customer experience, and service process. These dimensions are intertwining constituents of service innovation. Service innovations may involve more than one dimension, and changes along one dimension trigger changes in the others.

Service concept innovation refers to the new elements of the intangible offering presented to the customer, providing novel ways to organize a solution to customer needs or problems, often by recombining elements of existing services in a fresh configuration (e.g., Den Hertog, 2000). The interaction between the service provider and the customer is the domain of customer experience innovation. Specifically, as services are increasingly delivered through a combination of digital and physical touchpoints, innovations in the customer journey through the available touchpoints make the service more customized, interactive and easy to use. Lastly, service process innovation refers to the new or enhanced internal systems that allow service firms and their workers to deliver services to customers more efficiently and effectively (e.g., Miles, 2008). These innovations may introduce completely new elements in service delivery, or optimize and improve existing ones; they mostly take place back-stage, but may also be connected to customer-contact processes.

A critical factor underpinning all service innovation dimensions is new technology. The role of new technology has been discussed within the framework of service innovation from multiple perspectives (e.g., Barret et al. 2015), with some authors elevating new technology as a fourth dimension of service innovation (Den Hertog, 2000). Information technology has received particular attention as a fundamental enabler of service innovation (Barrett et al., 2015; Den Hertog, 2000; Miles, 2008). According to Barras (1986), new information technologies are first applied to incrementally improve the delivery process and efficiency of existing services. Then, these technologies are integrated into more radical process innovation that enhances the quality of existing services. Finally, new information technologies help generate completely new services. In keeping with this literature, information technology is conceptualized as a key enabler of service innovation. Enablers are factors that allow actors to do things that were not previously possible, by empowering them with capabilities and assets they did not have access to before (Normann, 2001).

The literature on new service development (NSD) success factors (e.g., Storey et al., 2016) offers additional elements to conceptualize the organizational enablers of service innovation. Storey et al. (2016)[ii] classify the most important organizational correlates of new service success. They include the characteristics of strategy, processes, teams, as well as other organizational characteristics (i.e. culture). Starting from this evidence, these factors are integrated into the service innovation framework as contextual organizational enablers of service innovation. Organizational enablers, together with technological enablers, facilitate the continuous design and redesign of new service concepts, processes, and customer experiences. Figure 1 synthesizes the conceptual framework of service innovation.

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Data-Rich Environments

The distinctive feature of data-rich environments is the ‘datafication’ of, potentially, everything (Lycett, 2013; Mayer-Schönberger, and Cukier, 2013). To clarify the term, to ‘datafy’ a phenomenon or event is to put it into a quantified format so it can be tabulated and analyzed. Datafication is associated with the concepts of dematerialization, liquidity, and density (Lycett, 2013). *Dematerialization* means that data are detached from the physical world. *Liquidity* indicates that once dematerialized, data can easily be manipulated, moved around, bundled and unbundled. The concept of *density* is associated to the convergence of data in a particular context, time and place to create value (Lycett, 2013; Normann, 2001). Density can also be thought of as re-materialization process that ‘brings data back’ to a real world application in ways that benefit a particular actor, in a given context (time/space).

Three commonly accepted features of data-rich environments are Volume, Velocity, and Variety (the 3 Vs) (e.g., Gandomi and Haider, 2015). *Volume* refers to the magnitude of datasets, which has emerged as the first major challenge in data management. *Variety* is the structural heterogeneity of datasets, defined as the variance in the types of data, in particular the unstructured data (i.e. text, sounds, images) that now represent a large share of the data produced by, for example, social media applications. *Velocity* equates to the reduced time latency between the steps of data generation, capture, analysis and decision-making (e.g., Pigni, Piccoli and Watson, 2016). With a vast amount of digital, mobile, and sensor-generated data, volume, velocity and variety keep increasing exponentially. Thus, while it is impractical to define benchmarks for the 3Vs, it is possible to conceptualize data-rich environments as high-volume, heterogeneous, and real-time.

Based on this definition, it is possible to distinguish between external and internal data-rich environments. External data-rich environment means that a growing share of what 'happens' around the world is captured by data, and these data are available for storage and use. Internal data-rich environment means that the information systems of a given organization are capable of capturing and processing a growing portion of all the data available in the environment. An internal data-rich environment only comes about when incumbent firms adopt big data management and analytics technologies. This often occurs after these organizations hit a '3V tipping point' beyond which traditional solutions become inadequate (Gandomi and Haider, 2015). For example, data management technologies shift from relational database management systems, which work predominantly with structured data, to scalable and distributed infrastructures and software frameworks (i.e. MapReduce, Hadoop) that make it possible to capture, extract, process, and analyze both structured and unstructured data (Chen, Chiang, and Storey 2012). In terms of analytics, new generations of techniques (i.e., text, speech, web, and network analytics) are introduced based on established mathematical models, machine learning and powerful new algorithms (Chen, Chiang, and Storey, 2012). The next section synthesizes the previous two in a preliminary framework that integrates data-rich environments and service innovation.

Connecting Service Innovation and Data-Rich Environments Frameworks

Through the developments described in the previous sections, big data management and analytics represent the *technological enablers* of an internal data-rich environment (Chen, Chiang, and Storey, 2012; Gandomi and Haider, 2015). In fact, technological enablers make it possible for incumbent service firms to work with dematerialized and liquid resources (data) with increasing volume, velocity and variety.

Data analysts and decision-makers increasingly operate in an environment where N=all and the number of variables is potentially infinite (Mayer-Schönberger and Cukier, 2013). Therefore, data on some key features of a problem or decision can be omitted, and less important ones can be added; data users can be channeled towards (or away from) certain inferences and actions, and creativity may be directed in certain directions or even stifled (Lycett, 2013, p. 384). *Data density processes* provide the mechanism for re-linking the dematerialized and virtual world of data-rich environments with service innovations developed in (and for) the physical world. Density expresses the extent to which data are mobilized for a specific combination of *time* (when things can be done), *space* (where things can be done), and *actor* (who can do what) (Normann, 2001, p.17), where service innovations can be located. The actor, or aggregator of value, can be an internal user of data (i.e. employee, manager) or an end user of the service. Data density augments the output of data analytics (i.e. statistical patterns, trends, relationships, predictions) with a sense-making process that makes data-driven insights plausible and actionable in business contexts populated with events, people, actions, and things (Lycett, 2013). Data density processes, as described above, are a fundamental component of a process for service innovation in data-rich environments, as they represent the intermediate link connecting technological enablers with service innovation opportunities. This conceptualization follows the structural contingency theory of the effect of information technologies on organizational design and performance (Markus and Robey, 1988). The adoption of data management and analytics technologies has a deterministic impact on how internal information processing, learning, and decision-making is organized (i.e. data density processes)[iii]. These intermediate processes help realize the potential value of the information technologies on innovation and organizational performance (e.g., Tippins and Sohi, 2003).

Finally, the role of *organizational enablers* is crucial because data-rich environments not only involve the modification of information technologies, but also a substantial transformation of organizational culture, structures, processes, roles and capabilities for incumbent firms (Sharma, Mithas, and Kankanhalli, 2014). These factors will play a specific role in service organizations, given the strong interdependence between the organizational context and technology in service innovation (Menor, Tatikonda, and Sampson, 2002; Nijssen et al, 2006). Specifically, they will influence the efficiency and effectiveness with which new enabling technologies lead to data density processes, and these processes in turn lead to ideate and develop innovative service offerings (Figure 2).

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Methodology

Research design and sample

There are two main elements to this study's research design. The first is a rudimentary conceptual framework, derived from the literature, as described above. The second is a qualitative study centering on semi-structured interviews with managers of large service firms. Following a naturalistic approach, our study focuses more on ‘what’ goes on in the research context, and less on ‘how’ events are socially brought into being (Silverman, 2014). Our interviews are topical as they look for facts, descriptions, and examples that help answer a set of specific research questions (Rubin and Rubin, 2012).

Our sampling is deliberately restricted to companies with a large customer base (ranging from 4 million to more than 30 million customers), that were not ‘digital natives’. These two characteristics offer the most suitable context given that our interest centers on the organizational issues associated with the link between data-rich environments and service innovation in incumbent firms. In addition, our sample represents the sizeable number of service companies that existed before the advent of big data. After generating a shortlist of potential target companies, the authors contacted the human resources (HR) offices of these organizations and sent them a short outline introducing the research. This led to an initial meeting with an HR representative from the companies that expressed an interest in the study. This meeting served to gain further access to managers for the interviews, and helped us identify knowledgeable people in the organization. Throughout the entire research process an HR representative acted as gatekeeper or company-designated liaison (O’Connor and Rice, 2013), which facilitated access to additional participants after each interview.

The sample companies are headquartered in either the United Kingdom or Italy, and compete both nationally and internationally in the following industries: utilities (electricity and gas), petrol stations, car sharing, postal services, telecommunications, banking, logistics and insurance. These industries are representative of big data sectors (Verhoef at al., 2016). The interview protocol followed three major lines of enquiry: i) the company’s journey towards adopting big data (i.e. What is ‘big data’ from your firm’s point of view? How far has your firm come in the process of adopting big data? Which steps has the company taken so far towards adopting big data? What are the next steps?); ii) the cultural, structural and organizational impact of big data (i.e. What impact did big data have on the company's culture and decision-making? How are big data technologies and analytical talents structured within your company? Which organizational units and levels are leading the implementation of big data projects? Have big data had an impact on internal organizational processes?); and iii) the contribution of big data to service innovation (i.e. Has the adoption of big data enhanced your company's ability to innovate your services? Can you give any examples of how service innovation opportunities have emerged from big data? What are the barriers and drivers of this process? Can you describe the innovations your company has developed by leveraging big data?). While the interviews were based on the common set of questions described above, in each case the interviewer followed up with other questions seeking examples, clarifications and probing into specific issues (Rubin and Rubin, 2012).

Data Collection and Analysis

Interviews took place between July 2015 and September 2016, were always conducted in the interviewee's office, and often preceded by a visit to her/his department and team. In all but one company, at least three knowledgeable informants from different functions involved in service innovation were interviewed (see Appendix). Specifically, the authors conducted 40 semi-structured interviews with managers of seven service companies; one interview was with a former CIO of one of these companies who very recently left after overseeing several projects related to big data. All interviews, which lasted between 45 and 90 minutes, were recorded and fully transcribed with the consent of the participants. Participants were guaranteed total anonymity; hence, individual or company details are not disclosed while reporting our results.

Initially, the researchers listened to each interview independently and compiled notes, later comparing them to identify an initial set of themes and ideas. Using the full verbatim transcripts, the authors then coded concepts (i.e., single ideas expressed by one or a few words), themes (i.e., summary statements, causal explanations, or conclusions), examples and events that related to our research questions (Rubin and Rubin, 2012). In the coding process, labels were assigned to portions of texts. Coding was initially based on the conceptual ‘bins’ of our rudimentary model: 3Vs, data management and analytics, data density processes, service innovation, organizational enablers[iv]. In identifying new codes, each idea or insight should be i) applicable beyond the specific firm/industry, ii) mentioned by multiple participants, and iii) lead to new and non-obvious conclusions.

Trustworthiness Criteria for Results Validation

During data collection and analysis, several approaches were implemented to attest the validity and reliability of our findings (Lincoln and Guba, 1985). To establish *credibility* the research started by building trust between the informants and the research team through an initial presentation of the research, the endorsement of a gate-keeping HR representative, and by ensuring confidentially and anonymity. In addition, different sources of information were triangulated by using multiple informants in six out of seven companies, and by crosschecking interview findings against other sources[v]. Negative case analysis was used by looking back at our propositions in hindsight to make sure the model provided a credible account for all companies, and to check that exceptional outliers did not emerge. The authors also collected feedback from all participants (members check), through follow-up telephone conversations, on the accuracy of the coding, and on how well the final model described their company’s scenario. There was general agreement among interviewees that the model reflected their views and was applicable to their company. This validation is considered the most critical condition for establishing credibility (Lincoln and Guba, 1985)[vi].

The *transferability* of our results to other contexts is aided by the clear choice of using large service companies in our sample that were not digital natives. This helps the reader determine whether our findings may apply to a new setting, and to clarify what type of adaptations may be needed. Our findings section includes quotes and offers precise definitions of emerging constructs to assist potential ‘appliers’ in establishing precise criteria for importing our results in other contexts. Following a common approach to ascertain the *dependability* (or reliability), an inter-coder agreement procedure was used, as per the guidelines suggested by Creswell (2013, p. 254). The authors coded all interviews independently and then compared all the passages they coded. Next, the percentage of passages coded using the same code word by all researchers was computed (inter-coder agreement). [vii] In our case, this percentage was 84%, which is higher than the threshold of 80% recommended for this technique (Creswell, 2013; Miles and Huberman, 1994). Finally, Lincoln and Guba (1985) suggest the implementation of an external audit of the research findings, conducted by an outside independent assessor, to support the *confirmability* of results. While the necessary raw materials for this process were assembled (audios, transcripts, and notes on methodological procedure), a full external audit of our results could not be conducted. However, as noted by Creswell (2013) this technique can involve substantial costs (time and money), and may be less of an imperative if reasonable evidence of triangulation, thick-description, member checking and peer debrief is provided.

Findings and Propositions

Data-Rich Environments and Service Innovation

Our findings support the view that data management and analytics technologies (i.e. an internal data-rich environment) enhance service innovation in incumbent firms. Effectively working with increasing volume, variety and velocity of data, incumbent service firms can access data-driven innovation opportunities that were not possible before. These include optimizing their service delivery process, modifying their service offerings in real-time for specific customer experiences, and generating innovative service concepts that address customer problems or needs in new ways. The findings from our interviews help us characterize the types of service innovations enabled by big data technologies, tools, and techniques (i.e. internal data-rich environments). *Customer experience innovation* is achieved through innovation in the customer touch-points involved in the service delivery (Berry et al. 2006). For example, based on customer insights derived from data integration, the number and quality of the customer touch-points may change creatively to match the customer context. The next quote exemplifies this element of customer experience innovation.

> *[W]e are looking for a much more interactive product, a product that will appeal more to younger drivers and can be managed through Facebook or through social media. So, the idea is that they can have most of their transactions through a different interface rather than our own… So, this would give the user the advantage that [he/she] is comfortable and [the service] is in an environment that they are familiar with, and it was easy for them to use and easy for them to engage with* (Head of Marketing, Company 5).

Customer experience innovation is also achieved through dynamic customization of the value proposition. This can be described as modifying the elements of the value proposition (i.e., service attributes and price) to match the characteristics and context of the individual customers. This type of innovation involves targeted and creative marketing actions aimed at retaining or delighting customers. Our interviewees mentioned customer churn prevention as a typical example of dynamic value proposition customization that can leverage the potential of big data and real-time decisions, as expressed in the quote below.

> *Let's say our customer S. has an electricity contract and her partner M. has a gas contract, both for the same house. They have a second house by the sea, but they don't have a contract for that. Through social listening tools…we saw that S. posted something about going to their seaside house…and she also 'liked' [competitor name]…Now I know they live in the same place, go on holiday together and there is a potential for churn. How can I enrich this information? I also know that he's a frequent flyer, he likes to spend points from airlines to fly free. On this intelligence I can design some actions, a cross-selling for the holiday house or an action to prevent churn, or since I know he likes to fly, in our loyalty scheme we have partnerships, why can't we use one we know our customer likes?* (Customer Service Executive VP, Company 2).

Our informants also reported examples of the impact of big data on *service process innovation*, i.e. innovations in the mechanics of service delivery that make the service itself more efficient or effective (Berry et al. 2006). This type of innovation leads to innovative elements of the service becoming embedded in the present and future operations that support the service offering. For example:

> *I think about innovations in maintenance. Once I have a tool that tells the engineer that a certain cable is likely to break down tomorrow, he will get there half an hour earlier and avoid a blackout. This is an epochal evolution* (Senior VP, Head of Country Market, Company 2).

> *Big data allow me to identify very quickly geographical pockets of bad payers, in that case I can start a campaign to enrich the range of payment options, I can ask marketing to come up with a promotion or new offerings that work with direct debit, so I can resolve the issue with the payment collection process* (Senior VP Sales, Company 1).

Finally, our informants described how their companies leverage big data to identify *service concept innovations,* which diversify the offering by reconfiguring elements of the service to address new problems, target new customers, and change the firm's competitive landscape. In this case, big data support the identification of completely new services or radically new ways to redesign the existing service offering. Two interesting examples are described in the following quotes.

> *We [postal service companies] live the paradox of the 'undelivered'. Because nobody is home anymore. We live this paradox because whoever delivers a letter or a parcel, can*

only drop a postcard because we're never there. This paradox can only be overcome with a 'smart address' and the ability to give the customer the option to change timing or location and to receive alerts regarding the delivery. …This is the theme, where managing a lot of data does not only lead to a selling proposition, it leads to new and better services (Head of ICT Group Governance, Company 3).

We're doing another innovation called [brand name], which is the Uber model, but for house repairs. So when you call us to say, "Come and check my central heating," that requires a booking, an appointment, scheduling, routing; a highly complex optimization problem, to say, "After you've fixed Mrs Smith's boiler, go to Mrs Brown's house etc". But if you just approached it differently, and you just thought of yourself as like Uber, but in that context, which is: "My boiler's broken. Who wants to come and fix it?" You remove this need of a very expensive forecasting, planning system and people, because you're taking the demand, and matching it with capacity. Now we just say "This person is on his way" (Director of Strategic Systems, Company 4).

Based on the arguments and examples reported above we argue that:

P1. Data management and analytics technologies are positively related to three types of service innovations in incumbent firms: service process innovation, customer experience innovation, and service concept innovation.

Data density processes

The direct-effect argument described above focuses attention on '*what*' new service innovation opportunities may arise in data-rich environments. A second, more indirect argument shifts attention to '*how*' service innovation is created, centering on the processes and conditions under which the potential of data-rich environments is translated into service innovation within incumbent firms. Our informants often used expressions such as 'getting more traction', 'bringing data down to earth', and 'asking the right questions' to describe the need for processes that transform the potential value of big data management and analytics technologies into new ideas and innovations. As described in the following quotes, finding a way to design these processes is a major challenge for service firms.

Once the [Hadoop] clusters are up, all the data you may need simply start flowing, so you can build your analyses and use cases... but at this point, from an organizational point of view, what you still need to have is a clear sense of what you want to do with the data (Chief Technology Officer, Company 7).

Many think big data means replacing a database with a bigger one that takes in more data. So there is a rush to adopt big data as the definitive technological solution. But if you carry on doing the same things you were doing before, in the same way, then the move to big data is useless. This is not clear to the majority of people who talk about big data or dive headfirst in these things (VP Group Data Office, Company 6).

In the early days, there was a lot more innovation because it was just simple innovation, and it was all based on what the customer wanted; now, it's more about: "We've got all this data, how do we make more out of the customer than we've got?" (Head of Outbound Services, Company 5).

Our work identified three distinct types of data density processes, which we label as *pattern spotting, real-time decisioning, and synergistic exploration*; our interviews shed light on these processes with regard to several characteristics (see Table 1). *Pattern spotting* is a density process that captures the extent to which data analytics and modeling techniques are applied to past data on a process or activity; the aim here is to identify data-driven solutions to solve problems or overcome inefficiencies. Pattern spotting primarily leverages the *volume* dimension of the 3Vs, but variety and velocity are important secondary dimensions, allowing more heterogeneous and updated variables to be included in the explanatory models. The main function of a pattern spotting process is to explain past performance or outcomes and help decision-makers devise new actions, such as process innovation improvements, that can be applied with a medium-term time orientation (i.e. until the process is further improved or changed). Here are two pertinent quotes from our informants:

To put is simply, I need to detect anomalies against a trend or against my objectives…data should bring up all phenomena and actions that had a strong positive or negative impact, which created a discontinuity. If it's negative, I want to spot the problem, if it's positive I need to understand the opportunity (Head of Cognitive Computing Programme, Company 6).

..without even knowing anything about the customer, just by looking at this data can you see a pattern in the data that will determine whether a complaint is likely to occur, or whether a repeat call is likely to occur, or whether they're [the customers] likely to leave us even?... We're just asking: is there a pattern in the data that tells you these things? (Head of Data Science Unit, Company 4).

Real-time decisioning emerged from our interviews as a density process that reflects the extent to which data analytics are applied to highly time-sensitive and context-specific situations to allow a fast response to market stimuli. Therefore, of the three Vs, real-time decisioning leverages *velocity* more than volume or variety, using present or near-present data as input. As a result, the outcome of the process provides support for short-term decisions that directly affect customer interactions, and allows companies, for example, to design and implement machine learning and automated decision systems. Thus, the main function of real-time decisioning processes is to tap near-real time data to predict likely future states where there is an opportunity to generate value through a fast, targeted response. Real-time decisioning processes are particularly useful for innovating customer experience and dynamically customizing value propositions, as described in the following quotes.

> *If I ask what's your favorite sport, 90% of males customers answer 'football'. However, from social media we can see that some play golf, because probably some friend invited them to...Golf is never going to be their favorite sport, but it is meaningful at a particular time, it has a temporary value. Decisions based on traditional surveys are dead, because they are based on a static picture, they're not natural... decisions based on real-time data capture the emotional involvement and, you know, this is the era of emotions!* (Chief Information Office, Company 2).

> *[W]e asked ourselves: why don't we try real-time decisions using Machine Learning? We put together customer need identification, perfect timeliness and top down rules that we as humans take time to process…So the idea was to build Machine Learning models fed with a quota of static variables and a quota of streaming variables, so when we get a streamed transaction we calculate a score, and above a certain threshold there is an event. The model needs to be able to talk to the campaign manager [system] so that in milliseconds we send a communication to the customer when the customer is most ready for it* (Head of CRM, Company 6).

Synergistic exploration is the most loosely structured of data density processes. It can be defined as data-enhanced marketing strategy creativity, namely the extent to which big data are used for imagining new services that have synergies with current offerings, customer needs, competitive conditions and predictable trends. The main input to synergistic exploration is data *variety*. In contrast to real-time decisioning, synergistic exploration aims to impact operations and performance of the service firm in the long term. The main innovation objective here is to search out possible new service concepts to add to the firm's current repertoire in a complementary way.

> *[Y]ou need synergies, you need opportunities. We might have perfect synergies with life insurance, for example, but that's a very difficult market to get into. So although you have synergies, there are other barriers that make it harder to enter. So I think, as with all things, you build yourself something like a score-card. You look at a number of things: whether there are technical synergies; whether there's synergies with your customer base, and therefore data synergies; the wider macro-economy, and whether there is an opportunity* (Head of Business Development and Chair of Data Board, Company 5).

We advance the following proposition on the role of data density processes:

P2. Data density processes (pattern spotting, real-time decisioning and synergistic exploration) mediate the effect of data management and analytics technologies on service innovation in incumbent firms.

Organizational enablers

Keeping our conceptual framework in mind, our interviewees were prompted to elaborate on the internal contextual conditions (e.g. cultural, structural and process-related) that facilitate or hamper their companies in transforming the potential of a data-rich environment into more service innovation opportunities. This led to the identification of two sets of organizational enablers, which operate as moderators at two different levels: one acting on the impact of technological enablers on data density processes, and another influencing the effect of data density processes on service innovation.

Organizational enablers of data density processes

Data-oriented culture. Several participants indicated two cultural conditions that create the organizational environment in which the potential of big data management and analytics is translated into data density processes. The first condition is the diffusion of a data-oriented culture throughout the organization. This cultural shift emerges from the interviews as the realization by business users (outside the 'data-science' units) that an experimental approach based on hypothesis testing, leveraging available data resources, will improve the performance of the business and the overall efficiency of the organization. Davenport, Barth, and Bean (2012) define a data-oriented culture as one where the entire organization values data-driven analysis and decision-making. Interestingly, informants often juxtapose this approach with a traditional mentality based on management information reports, when selected data were used to produce static representations, and embedded in traditional business presentations; these were the basis of retrospective sense-making exercises carried out without factual evidence. Along these lines, several interviewees named one major effect of the 'new' data-driven culture: helping personnel challenge long-held mental and behavioral routines by advocating the conviction that predictions and decisions should be supported by solid data analysis and modeling, while relying less on intuition and personal feelings. The following is an exemplary quote on this issue.

> *I think you can make up an explanation for anything but you don't know if you are right, the only way you know if you're right is by making a prediction and testing it...What our team is doing, and I'd like to foster a kind of cultural change across the organization, is making predictions, making bets basically. We're going to get quite a few wrong, I think, but that's fine because you learn just as much from that...I think the real benefit of doing this within data science, within our area, it's hopefully going to be bringing about more of a cultural change, making data science analytics more understood…and make it available for other people to use as well* (Head of Data Science Unit, Company 4).

Customer-centric culture. The second facet of cultural change is a customer-centric culture. Customer centricity is a relationship-oriented business philosophy that puts customer knowledge and customer value opportunities at the heart of every business decision (Shah at al. 2006). Customer centricity emerges because the process of integrating multiple datasets opens up the problem of agreeing on a shared definition of 'customer' among different departments and teams. Customer centricity is typically emphasized as a core value of marketing strategies. However, our findings suggest that a company-wide, customer-centric culture, is perceived by IT, operations, and data-science informants as central to *their own* role (rather than as a marketing issue). This is because customer centricity is necessary to align the 'unit of analysis' that works as the epicenter of the integrated data architecture, as captured by the following quotes by non-marketing informants.

> *Now we have a common lexicon that we did not have before. What does 'customer' mean to us? (...) It's a common lexicon, a common language, a common way of aggregating information (*Head of ICT Operations & End User Services, Company 1*).*

> *Within IT, what we want to implement is customer centricity. We are striving to integrate all our business IT infrastructures in order to build a unified backbone permeating all businesses, channels and products. (...) We want to achieve a unified customer ID, a unified data management system, a unified campaign management system, a unified CRM system and so on (...) To achieve this we must ensure that the customer is one (...) This is our logic of customer centricity* (Head of IT Governance, Company 3).

Adopting the customer as the 'unit of analysis' within the data architecture suggests the 'right questions to ask' and helps firms pinpoint relevant use cases that turn the volume, velocity and variety of big data into predictive models, fast-response decisions and exploratory behaviors. In fact, these questions and use cases are not driven primarily by technical hot issues but instead are identified in terms of impact on outcomes such as customer satisfaction, churn prevention, or new customer value opportunities.

In some instances in our study, this cultural change was not yet complete. In other words, the creation of integrated data architecture was not matched by corresponding shifts towards higher customer centricity and a more widespread data culture among non-specialists. In these cases, participants mentioned big data as a not-yet-realized opportunity, or even as a source of frustration due to lack of visible customer-related benefits stemming from big data investments, as captured by the passages below, followed by our proposition.

> *We have bought an aircraft carrier to land a few radio-controlled airplane models* (former CIO, Company 1).

> *We have a Ferrari and use it like a Fiat 500* (Customer Service VP, Company 2).

> *P3: The effect of data management and analytics technologies on data density processes in incumbent firms is stronger when the organization has: a) a diffused data-oriented culture; and b) a diffused customer-centric culture.*

T-Shaped Data scientists. According to all our informants, a highly emphasized change in their organizations, following the adoption of big data, was the hiring of data scientists. From our interviews, what emerges is that the skills of data scientists include a combination of strong analytics expertise and deep knowledge of the business. Interestingly, all our HR respondents and most of the interviewees from other departments cited 'social', 'soft' or 'people' skills as mandatory components of a data scientist's toolkit. This view of data scientists as socially skilled, analytical professionals is consistent with the expectations that analytics people play a crucial role in the diffusion of a data-oriented culture. In fact, even when data scientists are members of the IT Department, they are expected to act like 'problem hunters' in business lines, to demonstrate how business issues can be approached and handled more effectively through analytics. Specifically, service innovation tops the list of business issues that data scientists should help to activate. This is how one Head of Analytics described the activity of data science professionals in her company.

> *We essentially try to look at problems throughout the business. We will go around the entire business, sit in on meetings and try to look at problems that people are facing, decisions that need to be made and to try and ultimate those, try to put some science behind it, to put some numbers behind it…My side of the team, we do prescriptive modeling but we also go out into the business, we are the business-facing side of the team* (Head of Analytics Team, Company 5).

In contrast, several informants mentioned the lack of social skills of some of their data scientists as proof of an old-fashioned siloed view of the organization. According to this view, IT people simply act as 'number crunchers' without making any effort to try to share their competences, or to lend a hand to build a common, clear view of the business issues that sound analytics can effectively resolve. Therefore, we suggest that:

P4. The effect of data management and analytics technologies on data density processes in incumbent firms is stronger when data scientists have T-shaped skills.

Decentralized data analytics. Complementary to the skills of data scientists, their role and position within the organization also emerge from our findings as powerful organizational enablers of data density processes. Our findings suggest that by positioning data scientists in any department that may need them (i.e. Marketing, Outbound Sales), organizations can enhance the transformation of the potential of big data into density processes that drive service innovation. The primary motivation behind decentralizing analytics capabilities is to help disseminate a data-oriented culture, and to equip each department with analytic models and mindsets that are apt to strengthen data-driven decision-making and actions. Our interviews indicate that most firms adopt this initial option when they decide to pursue a ‘big data transformation’. Placing analytics capabilities close to business problems allows firms and their managers to test the ‘opportunity’ and ‘usability’ of big data, by observing how data management and analytics capabilities affect the efficiency and effectiveness of day-by-day processes. Moreover, by decentralizing analytics, ‘analog establishments’ get the chance to test their adaptability to the new data-oriented culture. One example of decentralized analytics is the agreement between Company 2 in our sample and a leading engineering university to recruit ten graduates from a Master of Science in data engineering, with the aim of assigning them to various departments as data scientists. In the words of the Head of HR of that company, data scientists are "*like a virus that must contaminate the entire company*." Data scientists working within business units are informally tasked with the educational role of unlocking the black box of analytics, and proving their underlying assumptions and rationale. With regard to this, we advance that:

P5: The effect of data management and analytics technologies on data density processes in incumbent firms is stronger when there is a data analytics unit that is decentralized across business functions.

Organizational enablers of service innovation

Data density processes represent the potential of big data in action. Extant literature (Lycett, 2013; Normann, 2001) underlines that these processes turn the power of data management and analytics into decisions and actions for a specific time/space/actor, that is, in our case, service innovation opportunities. In addition, our work identifies some organizational factors that enhance the effects of data density processes on service innovation.

Top management support. All the companies in our sample recognized service innovation opportunities linked to the data-rich environment. Our findings show that this link is reinforced by strong support from top management, which is often embodied in a single senior manager who champions the adoption of data-enabled innovation projects and helps remove obstacles that may come up in the organization. This champion may be a senior manager in the C-suite who is eager to push the adoption process, relying on successful previous experience of big data projects in other companies (most typical among CMOs), or on strong knowledge about new technological opportunities (most typical among CIOs).

Interestingly, most companies in our sample accompanied top managers' support with the creation of new organizational units tasked with building commitment towards data-enabled innovation projects in the wider organizational context. For example, Company 6 in our sample created a 'Group Innovation Unit', which reports to the CEO but has no hierarchical links with the different business lines. Group Innovation is responsible for identifying big data-enabled innovation projects (based on cognitive computing and machine learning technologies, for example), and championing them across the entire multi-country and multi-business organization. In addition, Company 5 established a 'Data Board', a group consisting of senior managers and heads of department, chaired by the Head of Business Development and reporting to the COO (who recently became the CEO). This group is responsible for big data projects, and plays several strategic functions: to establish a vision about big data, to prioritize projects, and to champion them throughout the organization. The Data Board is also in charge of disseminating information to the rest of the organization through formal documents, with the aim of raising internal awareness of big-data-driven innovation projects. With regard to this point, we advance that:

P6. The effect of data density processes on service innovation in incumbent firms is stronger when top managers support data-enabled innovation.

Customer-centric culture. Our data reveal that a customer-centric culture also plays a critical role in enhancing the effect of data density processes on service innovation. Interestingly, several informants from non-Marketing units stated that the success of data-enabled innovation projects was primarily due to the creation and diffusion of a customer-centric culture. In fact, both the common language created by customer centricity and the shared view of the customer generate more opportunities to focus data-enabled innovation projects at the forefront of customer value frontiers. Some informants emphasized that, compared to the past, today's innovation teams are empowered by stronger analytics capabilities, and as such are much better at avoiding service innovation trajectories with no clear or predictable impact on customer value.

Customer centric does not only refer to customers in our database, but also to prospect, potential clients. We want to effectively interact in a sophisticated way with all sources of information around our customers, which tell us something more about them, and allow us to offer new and better-tailored services (Senior VP Customer Management, Company 1).

P7. The effect of data density processes on service innovation in incumbent firms is stronger when there is a diffused customer centric culture in the organization.
Centralized data analytics.

It was previously argued that the position of data scientists within each business function facilitates the transformation of big data management and analytics into density processes. However, our findings demonstrate that creating a specialized data science unit within the IT Department enhances the ability of data density processes to generate actual innovations. The rationale here is to establish a unit of talented experts who can provide the whole organization with actionable solutions across various business issues. Our data validate the importance of this motivation among the companies in our sample. In fact, when a separate unit of analytics experts is formed within the IT department, exploratory behaviors for service innovation naturally emerge. Our interviews with IT personnel gave us numerous examples of how people in the centralized analytics unit tested predictive models unrelated to specific business requirements, but instead derived solely from a 'probe-and-learn' approach. This supplies business lines with new service ideas that diverge from the formalized innovation path of the firm. For instance, in Company 1, the IT Department started an 'Idea Lab' where they prototyped and tested a completely new service idea by connecting smart meters, smart plugs and other 'data-augmented devices.' In some cases, business units bought into these rapidly prototyped new products and included them in the innovation pipeline. Thanks to a specialized data analytics unit, the IT department may play a far more entrepreneurial role. An entrepreneurial IT department takes the lead in designing big-data-enabled service innovation projects, and then submits them to the relative business lines to be refined and included in the innovation development process. Thus:

P8. The effect of data density processes on service innovation in incumbent firms is stronger when there is a centralized data analytics unit within the IT function.

Marketing-IT integration. Whatever the position of data scientists within the organization, adopting big data offers an opportunity to reconfigure the relations between Marketing and IT. Our respondents envisage a new era of fruitful integration between the two departments, strengthening the potential effect of big data on service innovation. This is how one IT manager we interviewed described the Marketing-IT relationship in her company:

> *If a new service idea emerges, it emerges from a joint effort ….Compared to the past, today more and more ideas pop up 'together with'. It's no longer 'them' and 'us'. If Marketing and IT before were two completely separate worlds, very distant from each other, today it cannot be that way. We must be completely integrated. … Fast-forwarding into the future, I hope there will no longer be any difference between Marketing and IT (*Head of ICT Operations & End User Services*, Company 1).*

In most of our sample firms, these two units actively participated in the process of designing the data architecture; the heads of the two departments frequently and regularly meet in big data projects boards; the two units exchange formal documents about big data projects; analytics experts from the two units cooperate in designing explanatory and predictive models to solve business problems. In other words, a data-rich environment offers the opportunity to intensify the interaction between the two departments. Likewise, data architecture represents a boundary object for the two units; customer centricity gives rise to a shared cultural territory to make sense of the business; the two units cooperate on the same big data projects as peers with complementary competences. Thus, big data also offers the chance for closer collaboration between the two units. As theorized by Kahn and Mentzer (1998), interdepartmental integration comprises interaction and collaboration, where the former represents the structural side of integration, and the latter the unstructured affective side. Through interaction and collaboration, Marketing and IT increase their mutual understanding and develop reciprocal trust and commitment, while reducing dysfunctional conflict that may hamper the quality of service innovation. Therefore, we advance that:

> *P9. The effect of data density processes on service innovation in incumbent firms is stronger when Marketing-IT integration is high.*

Agile processes. Our interviews show that data density processes have an inherently project-oriented nature for two reasons. First, all companies in our sample have introduced big data through experimental 'pilot' projects before moving on to a more systematic transformation. As described in the above sections, these projects have mostly started with data management, moving on to implementing projects involving analytics for specific business areas, and finally deploying these models in the operations of the specific departments. The second reason is that big data imply a combination of investments in technology development, new capabilities and new roles, all of which require a typical project management approach. Interestingly, most of our respondents exhibit a manifest intolerance for established formalized roles and processes, which are perceived in stark contrast with the characteristics of velocity and variety of big data. Many interviewees cited the agile organization as a metaphor to neatly represent their expectations. Elaborating on this evidence, it may be argued that agile processes enhance the effect of data density processes on service innovation, consistent with Augustin (2005, p. 20) who defines agility as "the ability to deliver customer value while dealing with inherent project unpredictability and dynamism by recognizing and adapting to change". Our data validate the quest for role flexibility and self-organization as the crucial organizational pillars that focus the potentiality of big data on the provision of value to customers through service innovation (Davenport, 2014; Denning, 2015). In the words of one of our IT respondents (Company 3):

> *The traditional way has always been that marketing units within each business unit expressed their IT requirements. Corporate marketing collected those requirements in search of homogeneity. Then, they passed them on us; we identified the solution and gave it back to the business lines for the final implementation. ... Today's markets change so rapidly that we can no longer afford IT projects whose final release requires six months, one year; that is, you get the requirements and you release the solution one year later when it is completely useless. Therefore, we are beginning to work in a more integrated way, with less of a waterfall approach. The company is showing a strong willingness to change, to adopt a more agile logic. More importantly, a logic that's more customer-centric, more focused on the customer experience. That's what we're working on.*

P10. The effect of data density processes on service innovation in incumbent firms is stronger when the organization adopts agile processes.

Organizational practices. Our findings confirm that more and more often managers and employees are required to identify relevant data, customize datasets to their analytical needs, build models and deploy them in their decisions (e.g. Davenport et al., 2012). Guided by our conceptual framework, we prompted our interviewees to identify new organizational practices that helped them to extract value from these processes, by facilitating their link to service innovation opportunities. Our respondents repeatedly referred to the working practices of recombination and experimentation.

Recombination. Recombination indicates the activity of combining data from a variety of sources with the results produced by analytical models, personal expertise and business experience. In other words, recombination consists in overlaying data, models and contextual business expertise to develop innovative service insights. Here is one example.

> *We are assessing the launch of a new app through which we ask our customers to take pictures of their relevant possessions: cars, mobile phones, artwork and so forth. The idea is that they can build a catalogue of their valued assets. In fact, we can match the picture of the car with the data of the current value of those cars on the market, the same with their phones, artwork, etc. But we can also combine these data with the data we have about their financial assets. Hence, by combining all data together we have a full financial ID of each customer, not only what they buy but also what they possess. And if I match these data with their spending history I can predict when my customer is going to buy a new car…and anticipate that and sell to him a loan to buy the new car* (Head of Group Innovation, Company 7).

This example shows that in data-rich environments, decision-makers do not surrender to the power of technology nor do they abdicate their decisional responsibilities. On the contrary, when they develop a recombination practice by routinely interacting with data density processes, their decision-making becomes more evidence-based, leading to an improved service innovation process. Further, potentially limitless combinations leave ample room for human creativity in the pursuit of new service innovation opportunities.

Experimentation. Big data management and analytics allow firms to work with real-time data related to customer behaviors activated by customers themselves (e.g., calls to customer service, social media conversations, web surfing), or as a response to firms' actions. Experimentation refers mainly to the test of every combination of service features, prices, channels and communication content that can be delivered to a pre-identified set of customers to obtain behavioral responses (e.g., engagement and purchases). Based on our findings, experimentation strengthens the ability of personnel involved in service innovation projects to increase the effectiveness of data density processes, which in turn leads to improved service innovation processes, enriched customer experiences and new service concepts. Our informants provided us with numerous examples of the relevance of experimentation.

> *We do loads of tests. It's sort of our philosophy, even more so in outbound, it's constant tests. But we do a lot of work for other departments as well because there are always cases where we can help. So we're constantly testing. An example, a recent one, is the website behavior, when they don't complete the quotes. So we tested it in small scale, we made sure all the processes worked, we got the data, we got the MI set up so we know what's coming out of that process…* (Outbound Data Analyst, Company 5).

P11. The effect of data density processes on service innovation in incumbent firms is stronger when the organization adopts a) recombination, and b) experimentation practices.

Marketing capabilities. Data-rich environments endow incumbent service companies with an unprecedented level of customer knowledge. Indeed, our participants indicated that one of the most significant advancements brought about by big data is the ability to build a comprehensive customer 'ID Card'. This potentially includes every single piece of information about individual customers the company may deem useful, and offers the possibility to build decision-making rules and processes to act on this input. Thus, a finding of our study is that data-rich environments create *information asymmetry*, in stark contrast with the traditional view of customer knowledge, whereby companies know more about individual customers than individual customers know about themselves. Reflecting on how to unearth the potential to transfer this superior customer knowledge into service innovation and value, participants articulated the role of two marketing capabilities that can enhance the positive impact of data density processes on service innovation.

Customer education. This refers to service providers offering their customers information and skills that give them the ability to understand, evaluate and use their service in a better, more informed way (Bell and Eisingerich, 2007). Our interviews reveal that more and more often, service providers perceive the opportunity to inform customers and improve their service experience as an important value-adding capability, a requisite for exploiting the full potential of data density processes. In data-rich environments, where customers become increasingly aware of the information power of service providers, companies need to be able to transfer their knowledge back to customers in a way that they directly recognize and derive benefits from. In the words of a Data Analyst (Company 5):

> *I probably wouldn't get one [telematics black box] in this current form…But if I had like an app on my phone which said 'Your commute today if you leave now is going to take an hour longer than usual' because it knows where I drive, it knows what time I usually leave, so it can give that data back to me in a useful format I can consume, then all of a sudden I'm more willing to have that product because I get a benefit from it.*

Customer stewardship. Some informants pushed the boundaries of customer education to encompass the ability of service providers to inform customers about new ways of using their services that are economically more convenient, even if this means a loss of revenues, at least in the short term. In the context of big data, customer stewardship is the extent to which service providers are capable of leveraging their superior knowledge of customer usage patterns and other information to proactively offer a 'better deal'.

> *The issue is that the customer doesn't know, he's not aware. The idea is that you know the customer more than he knows himself, so in terms of design and sales of a new service, I can reach them and offer them something they did not know they needed…If you have a smart meter inside the customer's house you can say: 'Look, we see your consumption is strongly concentrated in time band 1, but you have a flat tariff. Now, perhaps we have a more convenient offer for time band 1 so that you can save, say, 20%.' This is a way to keep your customers for life, because in the next bill they see the actual savings. You maybe lose some money, some percentage of…but it's a lot worse if*

> *[competitor] comes and tells him: We think they got your plan wrong, son!* (VP Sales, Company 1).

Previous scholars defined customer stewardship as a mindset in which employees felt ownership of, and responsibility for, customers' overall welfare (Schepers et al., 2012). The concept was applied to face-to-face employee-customer relationships and linked to the knowledge and experience of the single employee, and the contextual characteristics of the interaction. Our interviews suggest that in a data-rich environment, customer stewardship moves from being an individual-level capability to an organizational-level capability that can intensify the impact of data density processes on service innovations, in terms of improved customer experience, and completely new service concepts. Therefore, we advance that:

> *P12. The effect of data density processes on service innovation in incumbent firms is stronger when the organization possesses a) customer education, and b) customer stewardship capabilities.*

Discussion

Unlike the bandwagon of studies that focus narrowly on the technological implications of big data, our work answers the call to better understand the broader set of organizational factors that underpin the service innovation process in data-rich environments. This study proposes a unified conceptual framework, developed from the literature and enriched by interviews with key informants, of the process and the moderating factors associated with the link between data-rich environments (i.e. 3Vs, data management and analytics technologies) and service innovation in incumbent firms (Figure 3). These factors encompass technological enablers, data density processes, organizational enablers, and service innovation dimensions. Our study reviews and integrates the conceptual frameworks of service innovation and data-rich environments, which were previously developed in isolation from each other. Further, our work complements existing service innovation research with a qualitative investigation of incumbent service firms that are transitioning from a traditional environment to a data-rich one. Our findings offer a series theoretical as well as managerial implications.

--- INSERT FIGURE 3 HERE ---

Theoretical Implications

First, our research addresses the theoretical gap regarding the process through which data-rich environments link to service innovation in incumbent firms. Building on previous literature, this study identifies the adoption of data management and analytics technology as a technological mandate (Markus and Robey, 1988) that can perhaps be delayed but not avoided. In line with prior observations from the literature (e.g., Chen, Chiang, and Storey 2012), the firms in our sample started their 'big data journey' with a thorough reconfiguration of the systems and IT solutions they used to store, manage and analyze data. While the data integration process is often described as a technical challenge, our research revealed that an integrated data architecture also becomes a significant boundary object around which different functions of the firm participate in the service innovation process (Carlile, 2002).

While technological enablers allow incumbent service companies to acquire and assimilate big data, data density processes make it possible to transform big data into service innovation, exploiting their inherent value. A major theoretical contribution of this study is to introduce the concept of data density as the intermediate process that connects data-rich environments with service innovation opportunities. The concept of density (Normann, 2001) is not new[viii]. This study, however, highlights the role of data density in the nomological network of innovation in data-rich environments, which was not exposed by previous research in this area. In other words, data density helps realize the potential absorptive capacity (Lam et al., 2016) embedded in big data management and analytics technologies. We propose three distinct processes that make this happen in practice: pattern spotting, real-time decisioning and synergistic exploration.

Each data density process drives the identification of actor/time/space combinations in which innovation opportunities emerge. While all three data density processes leverage velocity, volume and variety, each of them can be matched with a ‘dominant V’. In addition, they differ based on the temporal source of the data they use (past or present), and the time orientation of the decisions they support (short-, medium-, long-term). Also, the three data density processes each have main knowledge objectives (i.e. explain, predict, explore). Finally, though all three can support service concept, customer experience and service process innovations, each of them is more conducive to a specific type of service innovation.

The second area of theoretical contribution concerns two sets of organizational enablers that act as moderators of two salient relationships. The first set of organizational enablers (data oriented culture, decentralized data unit, and T-shaped data scientist) specifically enhances the connections between technology enablers and data density processes. A diffused data culture ensures that all members of the organization operate according to new norms and beliefs, such as the importance of evidence-based decision-making, and the need for business and data analytics to become two sides of the same coin in every organizational process. Decentralizing data units by putting specialized data analysts in business functions is a way to help contaminate the business environment with a new mindset, and promote data density by placing data expertise close to business problems on a daily basis. T-shaped data scientists are able to anticipate and embed the conditions for data density (time, space, actors) in the process of designing and implementing technology-based and data-driven approaches to service innovation. These three factors ideally point to a new organizational context populated by data-savvy employees and autonomous data users, a fundamental feature of innovative service companies in data-rich environments.

Data density processes expand the space for value creation opportunities that bridge the data-rich environment and the customer. However, link between data density processes and service innovation depends on a second set of organizational enablers (top management support, centralized data unit, agile development, recombination and experimentation practices, customer education and stewardship capabilities, and marketing-IT integration). Top management support contributes to sponsoring projects, coordinating information that promotes synergies and avoids the atomization of big data initiatives; such support can also train attention on specific service innovation dimensions (process, experience, and concept). Agile processes remove many structural barriers that may impede the implementation of innovation ideas. Recombination practices strengthen the ability of decision-makers to mix and match several service components and identify new and different value propositions to match customer contexts. Experimentation involves designing and implementing tests on a pre-defined audience with the aim of obtaining quick responses and feedback on new ideas.

Previous research identified an outside-in organizational culture and market knowledge competence as the key components of an organization's customer focus (e.g., Bharadwaj and Dong, 2014). Customer education and customer stewardship capabilities are expressions of these types of competences. In addition, while previous innovation research documented user involvement as voluntary and coordinated within a small network (Perks, Gruber, and Edvardsson, 2012), in data-rich environments a crowd of customers provide information on their needs on a continuous basis and very often without explicitly realizing it. Hence, customer education and stewardship will help address the customer information asymmetry of a data-rich environment by rebalancing the relationship in favor of customer benefits. This will prove increasingly critical as customers become more sensitive to privacy issues and more aware of their role in the data chain. Finally, the business world is replete with anecdotal reports of conflicts between Marketing and IT, mostly regarding the quest for flexibility and velocity of the former contrasting with the culture of standards and timeliness of the latter. Our study suggests that structured and unstructured mechanisms that enhance Marketing-IT integration enable service innovations in data-rich environments.

Finally, a customer-centric culture and a hub-and-spoke organization of the data unit act on both levels of the model. Customer centricity is a core organizational enabler of the whole process connecting big data technologies to service innovation. This is because the customer is the 'pivot' without which there is no way to articulate the time and space dimensions of data density processes (Normann, 2001). Thus, enriching the existing views of customers as drivers, or co-creators of service innovation, our research adds the concept of customers as value 'densifiers.' The hub-and-spoke organization of data scientists resonates with recent research showing that a separate innovation unit favors exploration and ambidexterity in service firms (Blindenbach-Driessen and van den Ende, 2014). Thus, our results suggest that a combination of decentralized and centralized data analytics units can simultaneously address the need for exploitative and explorative service innovations.

Managerial Implications

The technological discontinuation brought about by big data is not sufficient to produce innovation opportunities if the challenges related to cultural change, and organizational alignment are not successfully dealt with. Moving from this consideration, our findings provide managers in non-digital native service companies with numerous insights on how to turn the huge potential of data-rich environments into service innovation. The following themes summarize our key recommendations.

Make your company's internal environment data-rich. Our findings clearly show that investments in technological enablers are the first step in expanding a company's internal data-rich environment. Data management and analytics technologies provide the company with the ability of internalizing the volume, variety and velocity of external data-rich environments. Yet, managers should be wary that if they focus their efforts exclusively on the technological side of big data, they will exploit the innovation potential of data-rich environments only at a suboptimal level. Such potential should be fully realized through specific data density processes, supported by a number of organizational enablers.

Make data-driven insights acceptable and actionable. Data density processes are apt to mobilize big data for service innovation. However, they need to be calibrated according to specific time, space and actors involved in the innovation process. Managers may use pattern spotting to channel explanations of past outcomes into process innovation improvements, with a medium-term time orientation; real-time decisioning to leverage fast responses to market stimuli in order to design new or improved customer interactions focused on the short term; synergistic exploration to drive organizational creativity towards new service concepts to be launched with a long-term orientation.

Create the right culture, and ensure leaders' support. With the adoption of data density processes, organizations challenge long-held mindsets, capabilities, decision-making routines and collective working practices. Companies must demonstrate the utility of such processes for service innovation to overcome inertia and resistance by the analog-established power structure system and to favor the positive impact of internal data-rich environments on service innovation. To achieve this objective, companies may need to promote a customer-centric, data-oriented culture and get clear support and commitment by senior managers. In fact, a data-oriented culture validates the notion that service innovation must be driven by predictive, explanatory and exploratory capabilities, and helps generate a shared view of the market to concentrate innovation efforts on customer value creation and delivery. Senior managers can lead the transformation individually or as heads of new organizational units tasked with guiding the process; they can also act as accelerators to push the rest of the organization to commit to data-enabled service innovation projects.

Orchestrate analytic skills and foster Marketing-IT collaboration. Companies must leverage two potential roles that data scientists can play: helping business line managers understand the benefits of data-driven insights and decision-making for service innovation; exploring new patterns of innovation unrelated to the short-term requirements of the business lines. To leverage these complementary roles, companies may adopt a ‘hub-and-spoke’ design for the data science unit, with a centralized hub responsible for exploratory innovation, and decentralized spokes tasked with supporting business units. Moreover, data scientists should be hired and trained so that their technical skills are complemented by social skills. Our findings reveal that effective Marketing-IT integration also helps turn data density processes in service innovation opportunities. Companies should promote interaction and collaboration between the two functions. This can be done through a number of integration mechanisms, such as formal and informal exchanges of information, job rotation, joint participation on committees and boards.

Be agile, experiment and recombine. Our findings support the notion that a persisting siloed culture may represent the main obstacle to fully exploiting the potential of big data for service innovation. To avoid this risk, companies should redesign their organizational processes to disseminate agile processes and mindsets. Complementary to this redesign is the need to change daily working routines. Our findings suggest that recombination and experimentation help harness the potential offered by density processes and turning them into expanded service innovation opportunities. Our findings encourage companies to invest in training their personnel in various organizational units to develop agile mindsets and capabilities, and to apply recombination and experimentation in working practices.

Be your customer's educator and steward. Finally, our study urges companies to pay attention to the development of specific marketing capabilities. In data-rich environments an information asymmetry between the company and its customers naturally emerges, which may have a huge potential for informing service innovation. Our findings suggest that a way to channel this potential into successful service innovation is to task marketing experts who are particularly skilled at leveraging data density processes with educating customers, acting as customer stewards. These capabilities need to be developed through formal training.

Limitations and future research directions

Our work is subject to some limitations, many of which stem from the trade-offs between depth, generalizability and the practical constraints of qualitative research. First, our study is based on multiple interviews in seven incumbent service firms, so expanding the sample would improve the generalizability of our emerging framework. In particular, all our sample firms operate under some degree of public regulation (i.e. utilities, insurances, banks, TLC), which somehow limits their discretion in terms of data usage and service innovation. In addition, our sample is deliberately restricted to 'analog natives', so future research may bring further insights by comparing our findings with the organizational characteristics of their 'digital native' counterparts from less regulated sectors (i.e. retail). Finally, the duration of our fieldwork did not allow for a longitudinal design, for example by tracking the success of new service innovation projects. Future research may extend our findings in this direction.

In addition to the suggestions listed above, our model and findings point to new research opportunities. From a theoretical point of view, future studies can complement our approach in two ways. First, further investigation may enhance our topical approach by deepening the analysis of the social processes connected to innovation in data-rich environments (e.g., conflict, power shifts, and influence processes). Second, additional studies can integrate our organizational view with an expanded framework of service innovation that takes into account redefined competitive boundaries, and the long-term implications of the data-rich environment on the service ecosystem and the value chain.

From an empirical point of view, our work offers a series of research propositions that can be subject to future hypotheses testing. This will require further work on the operationalization of several new concepts, the most notable example being the three data density processes of pattern spotting, real time decisioning, and synergistic exploration. Here, our definitions and conceptualizations may be the starting point for scale development. In addition, future empirical investigations may provide additional insights into our hypothesized mediation and moderation effects. For example, empirical tests may establish whether data density processes uniformly mediate the effect of technology enablers on service innovation dimensions, or whether more specific patterns emerge. The role of data density as a mediator between data management and analytics and service innovation can also be empirically contrasted with possible alternative views (i.e. data density as moderator). Similarly, empirical work on our moderation hypotheses can tease out specific effects that were not conceptually anticipated. For example, it would be interesting to understand which organizational enablers are stronger moderators of the different data density processes and service innovation dimensions. Finally, future work can look at the impact of data-rich environments on the strategic infusion of service innovations in good-based offerings, to identify salient similarities and differences with the services context.

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Table 1.
Summary Description of Data Density Processes

	Data Density Processes		
	Pattern Spotting	**Real-time decisioning**	**Synergistic exploration**
Actor (Who does what)	Service employees optimize service delivery processes	Service employees and systems activate real-time offerings and communications for customers	Service managers identify new strategic innovation directions
Time (When Things are done)	Medium-term future	Real-time	Long-term future
Place (Where Things are Done)	Inside organizational processes and structures	At customer touchpoints	In a new market (by segment, product, geography, benefit)
Dominant V	Volume	Velocity	Variety
Temporal source of data	Mainly past	Mainly present	Both past and present
Main objectives	Explain, Optimize	Predict, Respond	Explore, Diversify
Main Service Innovation Dimension Supported	Service Process Innovation	Customer experience Innovation	Service concept Innovation

Appendix
Summary Information on Companies and Key-Informants

Company	Industries	Informants Formal Role	Number of Interviews
1	Petrol Stations Utilities Car Sharing	• Former CIO • Senior VP Customer Management • Senior VP Commercial Planning, Marketing & Innovation • Head of ICT Operations & End User Services • Senior VP Sales • Senior VP HR Business Partner • VP HR	7
2	Utilities Telecommunications	• CIO • Customer Service Executive VP • Senior VP, Head of Country Market • Head of HR Business Partner	4
3	Postal Services Banking Logistics TELCO	• Head of Corporate University • Head of ICT Group Governance • Head of Strategic Marketing • Head of Business Intelligence • Head of IT Governance	5
4	Utilities	• Head of Data Science Unit • Data Scientist (Machine Learning Specialist) • Head of Strategic Systems • HR Partner for Strategic Systems	4
5	Insurance	• Head of Marketing • Head of Recruitment • Head of Outbound Services • Head of Pricing • Outbound Department Data analyst • Head of Operations • Head of Business Development and Chair of Data Board • Marketing Data Analyst • Head of Data Analytics Team (IT)	9
6	Banking	• Head of Group Innovation • VP Group Data Office • Head of Cognitive Computing Programme • Head of Artificial Intelligence • Data Scientist • Head of Customer Insight • Product Manager • Head of Data & Analytics • Head of Internet and Mobile Project Development • Head of CRM	10
7	TELCO	• CTO	1
Total number of interviews			40

Endnotes

[i] Similarly, other attempts to link big data and business performance outcomes have considered supply chain operations (e.g. Sanders, 2016), or service marketing metrics (Kumar et al., 2013; Rust and Huang, 2014), leaving the relationship between data-rich environments and service innovation untapped or taken for granted.
[ii] We build on this particular meta-analysis because this work integrates previous important contributions along the same lines (e.g., Kuester et al., 2013; Papastathopoulou and Hultink, 2012). In addition to the categories of NSD success factors mentioned above, Storey et al. (2016) also include new service offering characteristics and marketplace characteristics. In this article we do not focus specifically on these two categories as they represent product-level characteristics or environment-level characteristics, respectively, deviating from the organizational level of analysis that we have adopted here.
[iii] Similarly, external data-rich environments (i.e. the 3Vs) represent an exogenous force that induces firms to adapt their internal data management and analytics technologies (Marcus and Robey, 1998).
[iv] In this respect, our approach to coding differs from that of grounded theory because the latter would let the codes emerge from the analysis without any reference to prior literature (Rubin and Rubin, 2012).
[v] For example, in Company 4 the informants showed us a meeting room decorated with data visualization plots printed on canvas and turned into contemporary art pieces as an artifact related to their promotion of a data oriented culture. In all cases, we used websites and other company documents (i.e. brochures, organizational charts) to corroborate information about new services or particular organizational characteristics.
[vi] The authors also had the opportunity to present our research during a specialized two-day academic workshop on innovation in data-rich environments, co-sponsored by two major US-based academic associations. During this peer-debrief session, feedback on our results was collected from expert academics and practitioners.
[vii]The aim of this procedure was to verify consistency in the interpretations of the same passages by different researchers, not to establish that every coder coded exactly the same passages, nor to prove that all coded passages include exactly the same words/lines (Creswell, 2013).
[viii] Previous information systems scholars included density as a feature of datafication (Lycett, 2013); others evoked density to reinforce the notion of co-production of value in an eco-system of interconnected actors (Michel, Vargo, and Lusch, 2008).

Figure 1.

Service Innovation Conceptual Framework

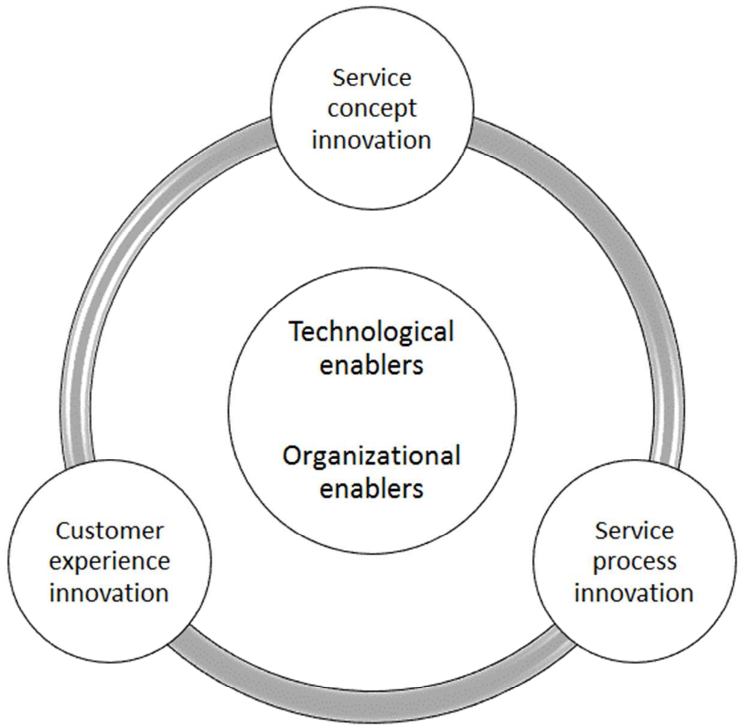


Figure 2.

Rudimentary Framework Connecting Service Innovation and Data-Rich Environments

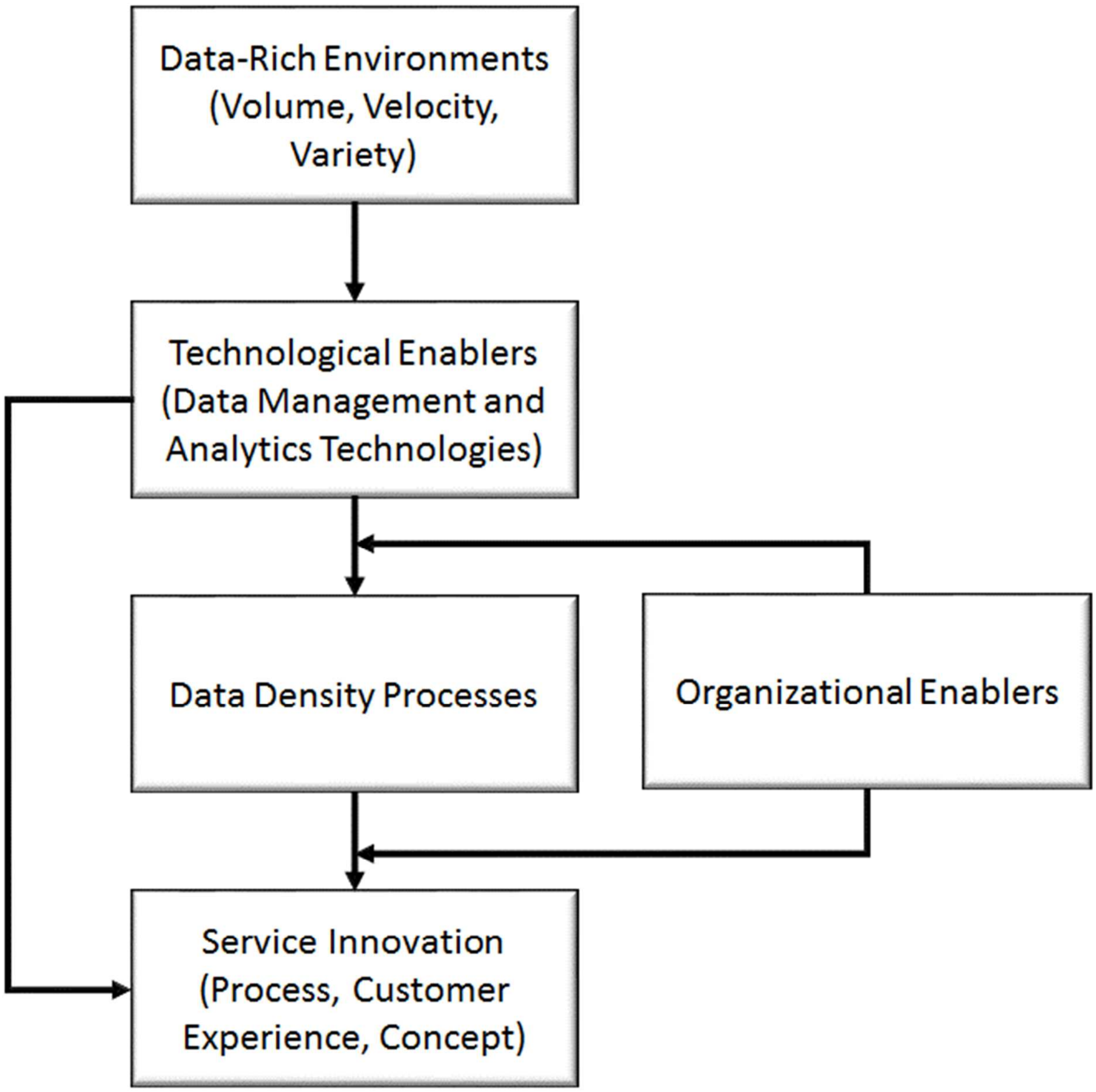
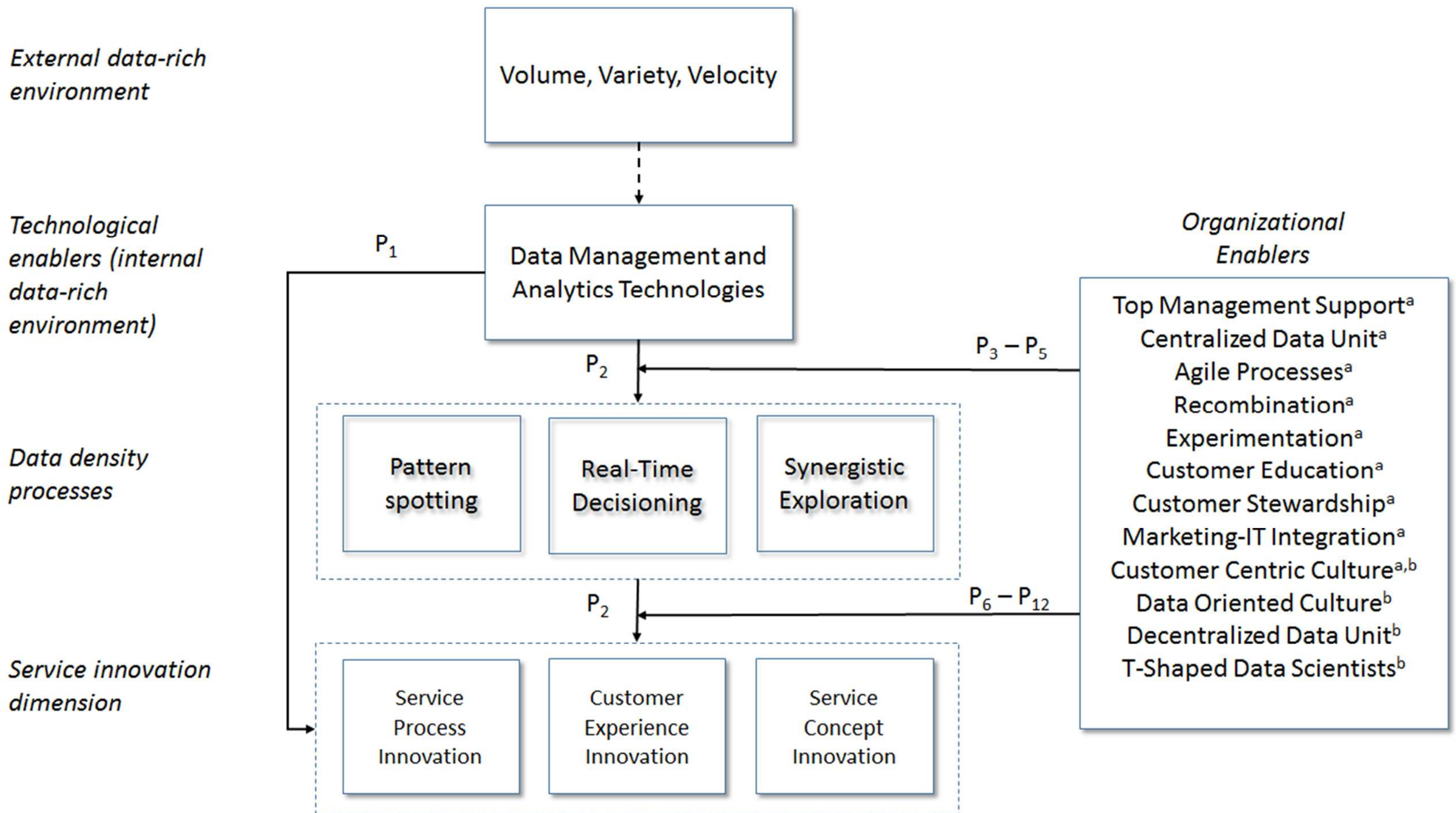


Figure 3.

Revised Framework Including Interview Findings



Notes: [a] indicates moderators of the relationship between data density processes and service innovation; [b] indicates moderators of the relationship between technological enablers and data density processes. The dotted arrow indicates a relationship that is included in the backbone model but not developed as a formal proposition.