Innovation and Big Data in Smart Service Systems

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Letter from Academia

As traditionally measured, services, which include everything from transportation to retail to healthcare to entertainment to hospitality and more, account for most economic activity. Taking a more modern view, we define *service* as value creation that occurs within systems of interacting economic actors. Service systems have been getting smarter over time, as big data analytics have been used to generate information and automate operations that create ever more value for people in the service systems. In this short letter, we describe some of our perspective on the use of big data analytics in smart service systems, suggesting one framework for thinking about big data in this context and outlining a set of research issues.

Keywords. Smart Service System, Big Data, Innovation.

1 Introduction

Service is everywhere. Taking a traditional view, services include transportation, retail, healthcare, consulting, outsourcing, entertainment, hospitality, and much more, accounting now for more than 80% of economic activity in the US and other industrialized countries (Spohrer and Maglio, 2008). Taking a more modern view, we think service includes all economic activity in which individuals, organizations, and technologies work together, applying specialized competences and capabilities to make all actors better off together than they are separately (Spohrer and Maglio, 2010; Vargo et al., 2008). On this view, service—also known as *value co-creation*—underlies all economic exchange (Vargo and Lusch, 2004). The key to effective service lies in arranging the capabilities among multiple actors or stakeholders so they can create the most value together (Maglio et al., 2009).

Specifically, we define s*ervice systems* as configurations of people, information, organizations, and technologies that operate together for mutual benefit (Maglio et al., 2009). Service systems differ from other types of sociotechnical systems in that they depend on entities sharing capabilities to increase mutual value. In this way, change in service systems results from rearranging where and how system capabilities are located (Breidbach and Maglio, 2015), often transforming the way systems work by embedding sophisticated capabilities into technologies, such as self-service technologies to generate more overall value (e.g., Campbell et al., 2011). In service systems, value creation is difficult to measure and anticipate: service systems depend not only on people, information, organizations, and technologies, but also on interactions among these, which has emergent consequences. We think a key problem in understanding service systems lies in understanding the critical role of people and their relationships with other components, such as information and technology (Maglio et al., 2015).

Service innovation results from transformations of existing service systems or establishment new service systems. It can often be achieved through offering a new core benefit or developing a new way to deliver a core benefit (Berry et al., 2006). Service innovation takes multiple forms in multiple industries (Miles, 2008), and is evident in traditional service industries and also manufacturing industries (Baines et al., 2009). It sometimes results from use of specific methods (e.g., Bitnet et al., 2008; Bettencourt, 2010) and sometimes requires organizational and cultural changes (e.g., Rothenberg, 2007; Reinartz and Ulaga, 2008). Sustainable service innovation requires continuous iterations of new service development, service operations, and service improvement (Kim et al., 2009). Stimulating service innovation is a timely research topic that has a large gap between importance and current knowledge (Ostrom et al., 2015) and *service science* emerged with the aim to achieve service innovation scientifically and systematically (Maglio and Spohrer, 2008).

A *smart service system* is "a service system capable of learning, dynamic adaptation, and decision making based upon data received, transmitted, and/or processed to improve its response to a future situation" (Medina-Borja, 2015). *Big data* typically describes large and complex sets of data representing digital traces of human activities (Manyika et al., 2011), and may be defined in terms of scale or volume (Zikopoulos, et al., 2012), analysis methods (Chen, et al. 2012), or impact on organizations (McAfee and Brynjolfsson, 2012). *Big data analytics* involves cognitive and computational processes that uncover patterns in big data (George et al., 2015). Smart service system innovation can take a great advantage of big data analytics (Medina-Borja, 2015) and recent studies show examples of the contribution of big data analytics to smart service innovation (e.g., Lim et al., 2015; Opresnik and Taisch, 2015).

Smart service systems are a kind of *human-centered service system,* meaning that knowledge, capabilities, and value are all determined by the people in the system (Maglio et al., 2015). Big data analytics can create human value in smart service systems in many ways; for instance, for customers, customer data may get converted into information that is useful in customer value creation processes in smart service systems (Saarijärvi, 2011), and for firms, customer data can be analyzed to understand patterns of customer behavior (Boyd and Crawford, 2011) to learn why customers make certain decisions or behave in certain ways (Huang and Rust, 2013) and to design new services or improve existing services (Lim et al., 2015). Use of big data can foster a mutually beneficial relationship between a firm, its customers, and possibly society in smart service systems (Kumar et al., 2013). Thus, a key problem in innovating smart service systems lies in taking advantage of big data analytics to create *human value.*

In this brief letter, we describe how big data analytics can help foster new service innovations, creating smart service systems by embedding human knowledge and capabilities in technologies to serve human purposes for effective value co-creation.

2 Using Big Data in Smart Service Systems

Cities around the world collect massive amounts of data related to urban living, and these data contribute to the production of useful information for citizens, visitors, city officials, and local employees (Caragliu et al., 2011). Automobile manufacturers analyze vehicle condition and driving data collected from onboard devices via telematics, and they provide various types of information to drivers, for instance, about fuel efficiency, safety, consumption, and navigation (Lim et al., 2015). Insurance companies collect patient data and provide healthcare-related information to patients to improve healthcare safety, reduce cost, and develop sustainable relationships (OECD, 2013). These are just a few examples of smart service systems enabled by big data analytics.

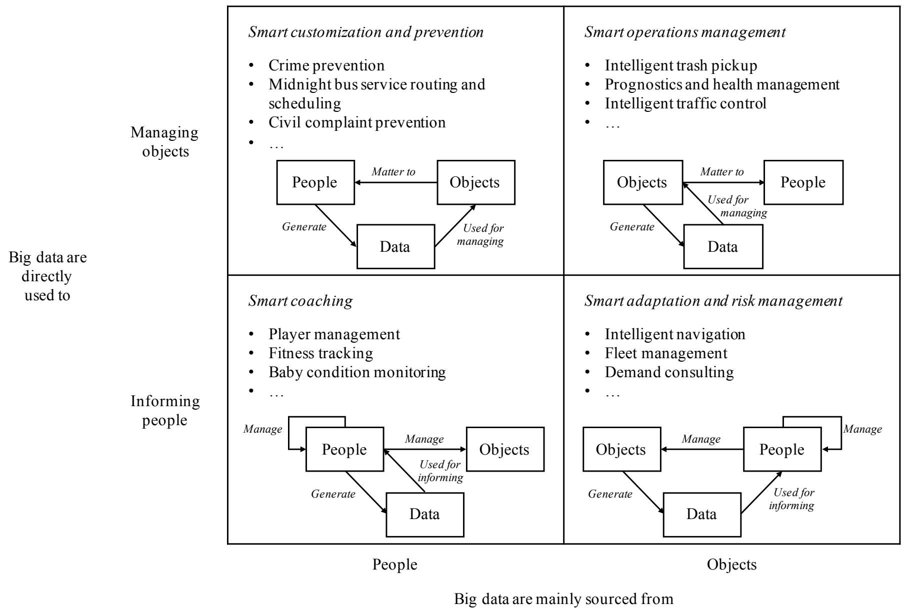

Fig. 1. Four ways to use big data in smart service systems.

We have studied big data analytics in smart service systems from many cases available in journal articles, books, technical reports, Internet news, and blogs. We found it useful to organize the cases by the source of data, either collected mainly from people or from objects, and by the use of data, either informing people to help people and manage objects or managing objects directly (see Figure 1). Our two-by-two matrix shows four categories of innovation in human-centered smart service systems. We describe each category in turn.

First, smart operations management (shown in the upper right of Figure 1) relies on data from objects (e.g. product condition, environment, and event log data) to manage objects (e.g. vehicles, infrastructure, and city administration). Cases in this category aim to improve operational processes of certain service systems by controlling objects within the system efficiently and effectively based on enhanced understanding of them through analysis of data. Representative examples include intelligent trash pickup, which collects data from trash bins using Radio Frequency Identification tags and schedules trash collection location and time (Purohit and Bothale, 2012); prognostics and health management, which uses the heavy equipment condition data to cope with potential product breakdowns and maximize product availability for stakeholders (Lee et al., 2014); and intelligent traffic control in Singapore, which collects data from roads and taxis to anticipate future traffic and control traffic lights for the citizens and visitors (Lee, 2013).

Second, smart customization and prevention (shown in the upper left of Figure 1) relies on data from people (e.g. human health, behavioral, and purchase history data) to manage objects. Cases in this category aim to understand problems and needs of people in certain service systems through analysis of data and then to customize system operation to specific needs or prevent problems. Numerous cases of smart cities (Caragliu et al., 2011; Kitchin, 2014) correspond to this category: Representative examples include crime prevention in San Francisco, which used crime records to predict future crime locations, patrol the locations, and prevent potential crimes (Lee, 2013); midnight bus service routing and scheduling of Seoul, which analyzed mobile call records and taxi-use data from the citizens and visitors to identify where they were and how they moved in the city late at night, enabling optimization of bus routes and schedules based on late-night demand (KLID, 2014); and civil complaint prevention of Busan, which analyzed 10 years of civil complaint records in a district and identified strategies to manage illegal parking, dust scattering from construction, streetlights, and other sources of citizen complaints (KLID, 2014).

Third, smart coaching (shown in the lower left of Figure 1) relies on data from people to help people (e.g., players, moms, teachers, and company employees) manage themselves and others (e.g. babies, students, and company customers). Cases in this category aim to provide evidence-based coaching or management based on enhanced understanding of human behaviors and context: Representative examples include player management, which involves data-driven evaluation and improvement of athletes, such as baseball players, golfers, and swimmers, using detailed data of their actions over time (Jung et al., 2010); fitness tracking using smart bands or other wearable devices, which collect data of daily life, such as behavior, health, and food menu data, to help people achieve specific fitness-related outcomes, such as walking 10,000 steps (Takacs et al., 2014); and baby condition monitoring, which collects data from babies and environment to give parents their status and predicted behaviors (http://www.sproutling.com/).

Fourth, smart adaptation and risk management (shown in the lower right of Figure 1) relies on data collected from objects to help people. Cases in this category aim to analyze the data about objects that affect specific human goals to help them adapt the objects and manage risks: Examples include intelligent navigation in Milan, which analyzes data on factors affecting traffic flow, such as real-time traffic situations, accidents, weather, construction, and event data from sensors placed all over the city, to provide navigation information to the citizens and visitors (Lee, 2013); fleet management, which collects data from transportation processes of trucks and uses the data to improve efficiency and productivity of the processes for drivers (Volvo, 2009); and demand consulting, which analyzes card usage records, types and revenue of retailers, and government data to assess which new types of businesses might be needed in any specific area for decision making by retail entrepreneurs (MISP, 2014).

People pay for goods and services to get jobs done, whether farming, driving, dating, or other business (Ulwick, 2005). Innovation is a perennial mission of firms, enabling jobs to get done better than before (Bettencourt, 2010). Our case analysis shows that big data analytics contributes mainly to the creation of useful knowledge to manage objects or inform people so that people can do their jobs (about either people or objects) better. In particular, as shown in Figure 1, big data analytics can create value for people *regardless of data source*. Our two-by-two matrix is a framework for understanding similarities and differences among the cases, helping us view big data analytics with human-centered and service-centered thinking. Exploration and exploitation of big data should be human-driven rather than technology-driven, and a prerequisite to big data use in a smart service system context is identification of the right information to generate human value. Our four categories can be applied to help innovate in any human-centered service system, such as in cities, health care, information and communication technology, education, and manufacturing.

3 Research Issues for Smart Service System Innovation

Smart service systems are everywhere. Yet relatively little is known about them and about innovation for them. Ostrom et al. (2015) identified and evaluated twelve service research priorities through roundtable discussions and surveys with service researchers around the world. Although all the priorities and related topics were deemed important, the study concluded that "using big data to advance service" had the largest gap between importance and current knowledge of the field. We also see a number of research issues for smart service system innovation among the fields of big data analytics, service science, and innovation management. These issues relate to design, evaluation, description, and automation of smart service systems.

First, consider service design. Service innovation depends on new or improved service ideas, concepts, processes, business models, and more. We see service design as the bridge that connects an opportunity or idea with full business development. Developing new methods for service design is a research area aimed at creating actual service value (Zomerdijk and Voss, 2010), and various service design methods exist, such as the TRIZ-based service design (Chai et al., 2005), multilevel service design (Patrício et al., 2011), and casebook-based service design (Kim et al., 2012). Although such methods may aid in service design in multiple contexts, none specifically address the design of smart service systems that rely on big data analytics. Another limitation of the current service design literature is that no method seems to exist for designing services starting from big data about customers. Such data-driven methods for service design could take the guesswork out of the customer understanding and enable the efficient design of information content for customers. The four categories proposed in this letter can be used as archetypes (i.e., design models) for the design of smart service systems. A data-driven service design method should consider the human-data-object relationship shown in Figure 1.

Second, consider service evaluation. Smart service system innovations are expected to develop in multiple industries with the rapid advancement of technologies for collecting data from people and objects (Medina-Borja, 2015). Developing scales for evaluating the quality of smart service systems from the perspective of human-centered big data use is another important research issue to improve emerging smart service systems. The perceptions of smart service system quality are not well-known, compared to those for traditional service (Parasuraman et al., 1988), electronic service (Ladhari, 2010), and mobile service (Akter et al., 2013). Novel quality scales may be required if customers perceive smart service systems differently from other service types. Such quality scales should consider the human-data-object relationship within smart service systems. Scale development itself may be facilitated by the use of big data that indicate customers' perceptions on specific smart services.

Third, consider service description. Using big data analytics effectively in service design and evaluation requires having a model that describes the service and the data together. Existing service description methods describe services from the perspective of service delivery processes, employee visibility, use of technology, and interactions among players involved (e.g., Bitner et al., 2008; Lim et al., 2012; Sampson, 2012; Teixeira et al., 2012; Lim and Kim, 2014), but cannot describe services based on a language of data. A generic model to describe a service with a set of variables that can be measured with a set of data, such as customer and context variables, could facilitate the design of smart service systems, data-driven service design, and evaluation of smart service systems; such a model would be useful in integrating different data analytics results (e.g., a statistical relationship between specific variables) to design and evaluate services as well as planning data analytics from a service-oriented perspective. Research on data-driven service description may involve analysis of existing service cases, such as the analysis shown in Figure 1.

Finally, consider service automation. Human actions in service systems can be categorized as informational, physical, and interpersonal actions (Apte and Mason, 1995), and the automation of these actions has evolved from automated teller machines of banking services to warehouse robots of shipping services and has made these services smarter. Big data analytics can contribute to automation of information actions: Decision-making and information exchange tasks in service systems can be substituted by big data analytics to create cognitive systems that can act on their own or provide support for people (Kelly and Hamm, 2013). The examples in Figure 1 mainly show the contribution of big data analytics to the automation of information actions in service systems. Physical actions, such as physical tasks and operations in service systems can be automated, for instance, through the use of robots and other control systems that substitute mechanical work for human work, such as rehabilitation and factory robots (e.g., Agarwal et al., 2015). Big data analytics can contribute to algorithms for controlling physical actions (e.g., Yun et al., 2014). Recent robot examples that interact with humans directly and emotionally (e.g., https://www.jibo.com) show that automation of interpersonal actions also can take a great advantage from big data analytics for recognition and prediction of emotion. Though the inseparable relationship between big data analytics and automation-based smart service system innovation has been discussed recently (e.g., Porter and

Heppelmann, 2014), little is known about such innovation. The human-data-object relationship in Figure 1 may prove useful in such research.

4 Concluding Remarks

Innovation in human-centered smart service systems will be enhanced by a shared vocabulary among disciplines, which is one of the main goals for the development of a unified service science (Spohrer et al., 2007; Maglio et al., 2015). Researchers have used different perspectives on human-centered smart service systems, such as data collection, analytics, and information delivery, but relatively little is known about how different perspectives can work together to create value with data. Such a framework could help build a theoretical background of human-centered smart service systems, stimulate applications of such services both in academia and by businesses, and foster human-centered service value creation with big data. For example, we see the potential for a new framework for *service-oriented data analytics* (SODA), a standard approach to collecting, transforming, and analyzing data to discover useful information for a service system. In the context of human-centered smart service systems, we can even see *cognition as a service* as a composable piece in larger systems (Spohrer and Banavar, 2015). Innovation in human-centered smart service systems depends critically on big data collection and analytics that serve specific human purposes and enable creation of specific human value.

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