Service Analytics: Leveraging Data Across Enterprise Boundaries for Competitive Advantage

Hansjörg Fromm, François Habryn, and Gerhard Satzger

Abstract The modern view on services focuses on the co-creation of value between providers and customers—leveraging knowledge, skills, and resources of both partners from an overall system point of view. This perspective goes beyond the typical customer integration in a traditional services context, thereby leading professional services firms to quickly adopt new methods to exploit this potential. This includes capturing, processing, and analyzing data produced by multiple actors within a services system with the objective to support strategy implementations and drive complex decisions—an area which we call "service analytics" in this paper. We describe the nature of service analytics and outline its distinctiveness with regard to business analytics. We subsequently provide a typology of its approaches based on the different types of data available in services systems. We finally illustrate the potential of service analytics by means of two application scenarios: customer intimacy analytics focusing on the service encounter as well as demand and inventory analytics which are concerned with customer usage.

1 Service Systems: Co-creating Value Across Enterprises

Undisputedly, modern economies have turned into "servitized" economies—with almost seventy per cent of the gross value added being derived from the tertiary sector (Satzger and Ganz 2010) and with an increasing number of industrial companies proceeding to engage in service-type offerings (Neely 2009).

H. Fromm (✉) • F. Habryn
KSRI/KIT, Germany
e-mail: fromm@de.ibm.com

G. Satzger
IBM, Germany

Analyzing particular managerial challenges for service enterprises, the distinction between products and services has traditionally been posing a significant problem for researchers and practitioners. In recent years, however, the insight started to prevail that products and services merely are extremes of a continuum of "solutions" that we can observe in the market (Engelhardt et al. 1993)—where typical service challenges do occur in the service-end of the continuum, but not exclusively there. The focus, therefore, has shifted away from service enterprises or industries to specific challenges to create, market, and deliver service-type solutions—regardless of the type of industry they belong to.

Most prominent—while still controversial—is the so-called Service-Dominant Logic proposed by Vargo and Lusch (2004, 2008) that advocates the perspective that value is not "embedded" in products or services, but rather is created by the knowledge, skills, and resources employed by both provider(s) and customer(s). The particular challenge then is the joint value-creation (co-creation of value) of partners aiming at incorporating potential contributions from both sides to come up with a solution that—from an *overall* system point of view—maximizes the generated value. This goes far beyond the typical customer integration in a traditional service context in that it elevates the viewpoint above the simple provider perspective. Moreover, it opens the view to analyzing and purposefully designing more complex service systems comprising larger numbers of stakeholders (Maglio et al. 2006; Spohrer et al. 2007).

Existing "disconnect": Looking at traditional service patterns, we realize that one of the key challenges obviously consists in making the knowledge, skills, and resources available at one integration point—i.e., to connect the partners. This gets evident looking at a simple example with data being one of the important resources to be shared: energy providers and their customers would both benefit from understanding and reacting to the consumption patterns in an energy system. So far, however, individual consumption is neither measured "real-time" nor frequently communicated to the provider limiting insights and preventing arrangements like incentivized contracts within the system. Energy is flowing from the provider to the consumer, but no information regarding its usage is flowing back from the consumer to the provider. Similar situations can be found in other industries. Automotive manufacturers, car dealers, and vendors of value-add services around the car do not know much about the usage of their products and services by the customers. Doctors and other medical service providers do not know about their patients' behaviors and health status once they have left their offices.

Instrumentation to overcome the "disconnect": Modern information and communication technology is helping to create a "service system wide" view and, thus, exploit the inherent potential as evident in our energy scenario above: rather than manually reading consumption values once a year, energy meters could provide values let's say every 15 min—creating about 35,000 times more data than before. At the same time, this data could centrally be made available and energy providers could manage capacity (e.g., by anticipating expensive peak periods) as well as influence capacity (e.g., by incentives for off-peak consumption)—to the advantage of all parties: lower energy prices for consumers, higher profits for providers, and

environmental benefits for all. The "disconnect" will presumably be overcome in the next few years with the emergence of new instrumentation technologies. An increasing volume of data will be collected either by the users/customers themselves (e.g., through mobile/smart phones) or by technologies like smart metering in energy services, telematics in automotive and mobility services, RFID in logistics, condition sensors in engineering, data capture solutions in healthcare, etc. The further dissemination of electronic networks, led by the internet "revolution," will increasingly enable the sharing of the captured data across organizational boundaries and support their availability at the point of decision.

Where data is available already today, the potential is clearly visible—as in e-services (services fully rendered over the internet): by design, these services require connectivity between providers and customers. So, e.g., customers visit the provider's web pages in order to obtain the service. Thus, the provider is able to analyze the customers' usage characteristics at any level of detail. Typical data of interest are the overall number of page visits, the number of page visits per customer, the time intervals between page visits, the path that an individual customer takes through the web site, etc. (see Srivastava et al. 2000; Han and Chang 2002). With this data, the provider can perfectly analyze the behavior and preferences of individual customers, can make recommendations, can assess the general acceptance and attractiveness of his web offering, and discover possible usability problems related to navigating and finding information on his web pages.

For this process of capturing, processing, and analyzing data taken from a service system—in order to improve, extend, and personalize the service and create new value for both the provider and the customer—we use the term *service analytics*.

2 Service Analytics: Nature and Typology

In the following, we first clarify the notion of analytics and then position service analytics as well as dissect this new field via a typology of its approaches.

2.1 The General Notion of Analytics

There is no single agreed-upon definition of the term "analytics." Some authors like Kohavi et al. (2002) use the terms "analytics" and "data mining" interchangeably. Others like Davenport (2006) use "analytics" as a synonym for "business intelligence." Some dissent is particularly related to the question if analytics should include or exclude data management and reporting technologies: Davenport and Harris (2007) distinguish between "access and reporting" and "analytics," both seen as subsets of business intelligence.

For our purposes, we consider data management and reporting as the "basic analytics" which are a prerequisite for "advanced analytics" (see Kobielus 2010) built on methods from statistics and operations research.

Basic Analytics include reporting solutions based on data warehouse and data marts like standard and ad hoc reporting, online analytical processing (OLAP), queries, drilldowns, and alerts (see Chaudhuri and Dayal 1997).

Advanced Analytics comprise various methods from statistics and operations research which can be *descriptive*, *predictive*, or *prescriptive* (INFORMS 2012). Data mining and machine learning algorithms like clustering (segmentation) and association can be used to identify similarities between customers (e.g., for recommendations). Text mining algorithms are the basis for customer experience, sentiment, and complaint analysis in unstructured data sources like blogs on the internet. Temporal data mining algorithms are able to discover sequential usage patterns, e.g., in the browsing behavior of customers on a provider's web pages. Visual analytics and visual data mining can be used to provide a clearer view and understanding of relationships within a complex service system. Time series forecasting, regression analysis, and artificial neural networks are the most widely known methods for prediction (e.g., of service demand) and trend analysis. Finally, methods like simulation and mathematical optimization can be used to prescribe or recommend the best possible actions for improvements.

Davenport and Harris (2007) consider analytics the next source of competitive advantage. A recent survey by Lavalle et al. (2011) revealed that top-performing organizations are using analytics five times more often than low performers. Davenport and Harris (2007) point out that the competitive advantage of analytical methods increases as their "degree of complexity" (from basic to advanced) increases.

2.2 Service Analytics as Analytics to Support Service Systems

The adoption of analytics applied to service systems is still in its infancy. Some areas like web analytics are more advanced, some other areas like healthcare analytics are just starting. The goal is to apply basic and advanced analytics to an entire service system in order to generate the highest benefits for all partners according to the value co-creation principle.

In most industrial application areas, this goal has not yet been reached. We observe different adoption and maturity levels along two dimensions resulting in a Service Analytics Typology (see Fig. 1).

Typically, *data inside the service provider's organization* are easy to obtain. They are typically accessible through the provider's financial and operational planning systems like Enterprise Resource Planning (ERP) and Human Capital Management (HCM). Accounting and performance reporting (e.g., on the utilization of service resources) are typical examples for basic analytics applied to data inside a company (provider data). Workforce Analytics describe the application of
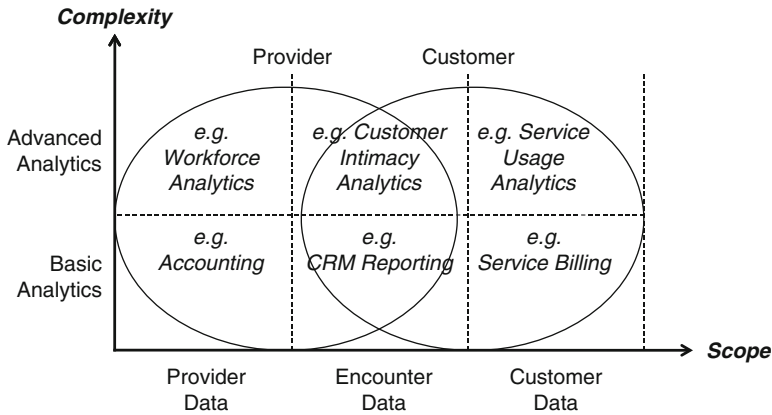
Fig. 1 A typology of service analytics approaches

advanced analytics to workforce planning and scheduling (see Mojsilović and Connors 2010).

Data related to the "service encounter" (see Payne et al. 2007), i.e., the interaction between service provider and customer, can be retrieved from Customer Relationship Management (CRM) Systems. CRM systems are widely deployed in the industry, but few companies use their systems to capture data on activities and interaction patterns in sufficient detail to allow advanced analytics to be applied. Our first example below, however, will illustrate the potential and reach of innovative approaches.

The availability of *data related to the use of the service* by the customer (customer data) is still limited in many cases. We were talking earlier about a "disconnect" between service provider and customer. If service usage data are captured at all, then this typically happens only outside the boundaries of an enterprise. As stated before, ICT may increasingly assist to overcome this "disconnect" in the future. These technologies, however, will generate an exploding amount of data. Service providers will encounter considerable ICT challenges (processing power, storage) in capturing the full potential of this "big data" (McKinsey 2011). High efficiency and speed are required from intelligent algorithms to process and analyze vast amounts of data. The application of advanced analytics to big data will become an immense opportunity for service companies to improve their decision making processes in the future (see White 2011).

A key societal question, though, is if the customers want to share their usage data with the service provider. Security and privacy concerns are the biggest obstacles to be overcome. The future will tell if providers are able to demonstrate to their customers the value and benefits of sharing data with them—and are able to prove that they handle this data with highest responsibility and care. Only then, a trustful relationship between the provider and the customer will be established, which is essential for achieving a common objective.

3 Service Analytics in Practice

We have selected two examples for Service Analytics from different areas of our typology. The first illustrates the use of advanced analytics in the context of customer intimacy (encounter/relationship data), the second explains the application of advanced analytics for service parts forecasting and inventory optimization based on detailed usage patterns (customer data).

3.1 Customer Intimacy Analytics

A recent survey conducted with 1,500 chief executive officers worldwide established that today "successful CEOs make customer intimacy their number-one priority" (IBM Institute for Business Value 2010). Customer intimacy (see Treacy and Wiersema 1993) has gained momentum over the last years as the ability to capture customer needs and to tailor provided solutions accordingly has become a key success factor also in the B2B space. However, even though CRM systems are well established today, they do not provide the appropriate means for supporting the implementation of a customer intimacy strategy: "the role of customer intimacy has been under-investigated" (Liang 2009) from an IT perspective. In particular, the measurement and management of customer intimacy still lacks analytical support.

Recent work on "Customer Intimacy Analytics" at the Karlsruhe Service Research Institute by Habryn et al. (2010) has addressed the question how existing CRM systems can be complemented with service analytics to assess customer intimacy by leveraging operational data available in the provider's information system. Service analytics enable the evaluation of the key aspects of a customer intimacy strategy: the acquired customer knowledge and established customer relationships as well as their impact on business. Therefore, service analytics allows providers to better assess progress and success of their customer intimacy strategy with different customers.

The first step of the analysis is concerned with the extent to which the activities and interactions between the provider and customer employees have improved the knowledge of and relationships with the customer *(acquired customer intimacy)*. Activity and interaction data which is related to the service encounter is captured from the provider's CRM system, which automatically records phone calls, emails, letters, and meetings. From this data, statistical information on specific interaction patterns such as frequency, regularity, intensity, and mode are derived. In parallel, information related to the acquired customer knowledge and established customer relationships are empirically gathered by means of surveys. Machine learning algorithms are subsequently applied to correlate the interaction patterns found in the dataset with the acquired customer knowledge and established customer relationship values returned from the survey: the result are calibrated, CRM-data based
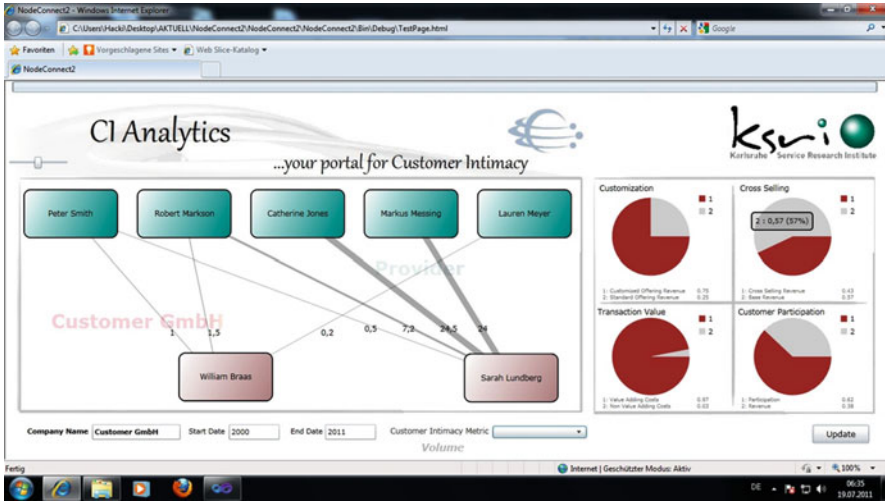
Fig. 2 Customer intimacy dashboard of KSRI-Solution *CI Analytics*

metrics allowing to assess the degree of customer intimacy. These findings allow an organization to gain insights on how to best establish, maintain, and enhance customer relationships as well how to effectively acquire customer knowledge by optimizing the customer interactions and activities.

The next step investigates to which extent the service provider has turned these acquired customer knowledge and established customer relationships into better solutions, improved service, additional sales, and higher customer satisfaction. This is called the *leveraged customer intimacy*. Several indicators for it have been conceived such as the percentage of customer participation in solution development, the percentage of customization in solution offerings, the percentage of cross selling of overall sales, or the reduction of transaction costs. These indicators are calculated upon available project and revenue data related to the service encounter. The solution, thus, allows to accurately estimate the business impacts resulting from the adoption of the customer intimacy strategy.

Figure 2 illustrates the customer intimacy dashboard which has been prototypically implemented. While the left hand side provides visualized information on the relationships established between the provider and customer employees, the right hand side depicts four of the conceived customer intimacy performance indicators.

In summary, the "Customer Intimacy Analytics" solution applies the service analytics concept on data related to the service encounter in order to support the assessment and monitoring of the customer intimacy strategy with different customers. It thereby supports the allocation of the provider's resources as well as the planning of the provider's investments with regard to its different customers.

3.2   Demand and Inventory Analytics

Our second example describes a situation where advanced descriptive, predictive, and prescriptive service analytics are applied to customer usage data. A provider of automotive after-sales services operates a distribution network to supply his customers and service personnel with spare parts. Inventories are kept in the warehouses to cover uncertainties in the demand. The provider's objective is to secure the availability of parts while keeping inventory costs at the lowest possible level. This may be considered a well-understood task, having been addressed by logistics and industrial engineering researchers and practitioners for decades—however, the performance of spare parts distribution networks is still poor in many cases, and companies are sitting on high inventory levels to compensate for this poor performance.

Studies have shown that companies often rely on either "rules-of-thumb" or standard ERP systems with less sophisticated algorithms for inventory management (see Wagner and Lindemann 2008). For customer intimacy we have shown that CRM systems can be enhanced with advanced analytics to provide additional value. Similar observations apply also to inventory management: ERP systems can be enhanced with advanced analytics to significantly improve the availability of materials and to optimize inventories.

The first step is to derive knowledge about current and future demand. The best source of information is the orders for spare parts that the customers have sent to the provider. These orders are kept in the provider's ERP system and are typically available several years back—they virtually depict the usage of customers. Advanced statistical analyses of historical demand data provide detailed information on demand level, variability, trend, seasonality, and sporadicity (irregularity). Figure 3 shows a typical demand pattern for a particular spare part, together with its statistical characteristics. Demand can be influenced by external factors like weather, temperature, economic cycles, promotions, holidays, and many others. If data on such external data are available, correlations between these factors and the demand can be identified. The prediction of future demand could now be viewed as an extrapolation of the historical demand, adjusted by the influence of the external factors.

Descriptive and predictive analytics provide demand forecasts for each individual spare part. The demand forecast is one input for inventory optimization. Other inputs are cost factors like ordering costs or inventory carrying costs including warehousing and capital costs. Inventory theory provides a variety of methods to determine the optimal inventory level for each individual part, together with optimal reorder points and reorder quantities.

The value of applying advanced analytics for demand forecasting and inventory optimization has been proven many times in industrial practice (see Korevaar et al. 2007). Forecast quality could be improved and inventory levels reduced by typically 15–25 %, sometimes even more. At the same time, the availability of parts and materials could be significantly increased. Higher availability reduces the
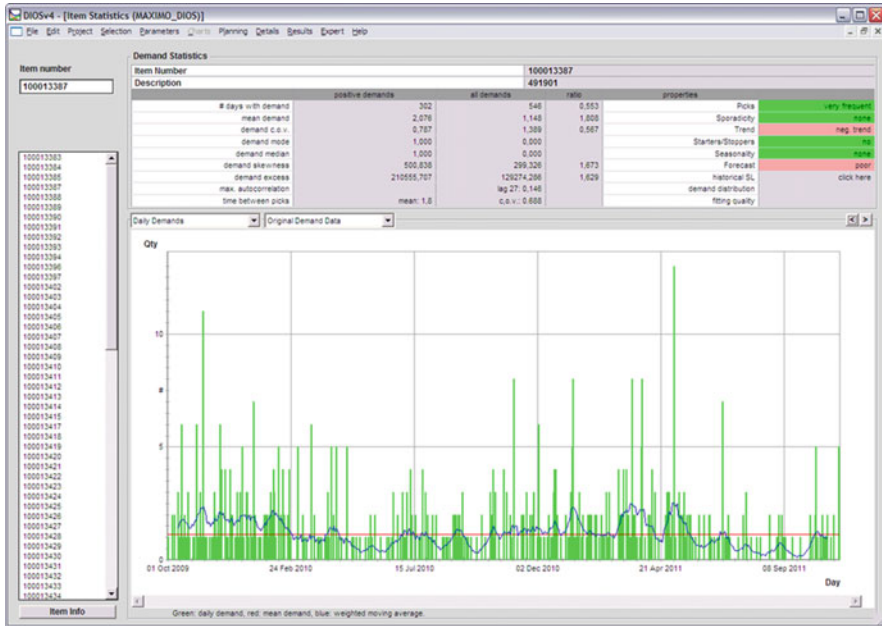
Fig. 3 Typical demand pattern in a service parts environment

customers' waiting time for parts and thus the downtime or performance degradation of the customers' resources (car, machine, etc.). Lower inventory levels reduce the logistics cost and lower the working capital of the supplier. This example demonstrates again that service analytics can be applied in an economic environment for the benefit of both the customer and the service provider.

4 Conclusion

In this paper, we propose to define service analytics as the application of analytics for service systems in which value is co-created by the provider and the customer. Service analytics combine provider data, customer data as well as service encounter data in order to improve, extend, and personalize services, thereby creating added value for both the provider and the customer. Through the adoption of the service system view, service analytics enhance the potential of business analytics and become a key solution for contemporary challenges such as resource allocation, usage optimization, and any complex decision making processes involving multiple stakeholders and requiring the system view. The success of service analytics is, however, heavily depending on the availability of exploitable data and, thus, relies on the readiness of the provider and customer to share this data and interconnect

their information systems for achieving a mutual benefit. The shift from a transactional to a relationship approach to a business, in which partners trust each other, is, thus, a key factor for the future success of service analytics.

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