Building Dynamic Service Analytics Capabilities for the Digital Marketplace

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Abstract

Service firms are now interacting with customers through a multitude of channels or touchpoints. This progression into the digital realm is leading to an explosion of data, and warranting advanced analytic methods to manage service systems. Known as big data analytics, these methods harness insights to deliver, serve, and enhance the customer experience in the digital marketplace. Although global economies are becoming service-oriented, little attention is paid to the role of analytics in service systems. As such, drawing on a systematic literature review and thematic analysis of 30 in-depth interviews, this study aims to understand the nature of service analytics to identify its capability dimensions. Integrating the diverse areas of research on service systems, big data and dynamic capability theories, we propose a dynamic service analytics capabilities (DSAC) framework consisting of management, technology, talent, data governance, model development, and service innovation capability. We also propose a future research agenda to advance DSAC research for the emerging service systems in the digital marketplace.

Keywords
Dynamic service analytics capabilities (DSAC), service systems, customer experience, big data, research agenda

1. Introduction

The progressive digitization of organizational processes and socio-technical interactions is elevating the role of 'data.' Some term data as the 'oil for digital economy' (Wedel and Kannan 2016) and other term data as an 'asset' (Davis and Patterson 2012). The characteristics of big data are themselves evolving from 3Vs to 7Vs, namely: volume, velocity, variety, veracity, value, variability, and visualization (Mikalef et al. 2017). Wedel and Kannan (2016) synthesize that big data, coupled with analytics, presents a value continuum that ranges from information-value to decision-value. According to the International Data Corporation (2019), the momentum for big data analytics (BDA) is well on course to achieve US$274.3 billion revenues by 2022, with a 13.2% compound annual growth rate. More than half of all these BDA revenues will be from the service sector, including IT ($77.5 billion) and business services ($20.7 billion) are the two largest categories. These findings substantiate the explosive growth and interest in harnessing the power of data and analytics for research in the digital economy (Ransbotham and Kiron 2018). Although big data research has gained momentum in recent years in various fields of business (Ferraris et al. 2018a; Akter et al. 2019b; Rialti et al. 2019; Mikalef et al. 2020; Wamba et al. 2020), no major research on service analytics capability has appeared in recent years. Reflecting on this significant gap and driven by the recent call for research on digital transformation in the service (Verhoef et al. 2019; Davenport et al. 2020; Grewal et al. 2020; Kumar et al. 2020), this study conceptualises a service analytics capability model using dynamic capability theories (Helfat and Peteraf 2009; Helfat and Peteraf 2015; Yasmin et al. 2020) for the digital marketplace.

This paper explores where service analytics fits within data-driven markets and what capabilities are needed to derive informational and decisional value. Increasing digital transformation is placing unprecedented pressure on service providers to dynamically adapt their services in (near) real-time to meet the customer needs (Motamarri et al. 2017). To tackle these challenges, service providers have to develop more in-depth perspectives about their interactions with customers and/or service encounters. Service systems use resources such as people, technology, organization, and shared information to satisfy customer needs better than competitors (Akter et al. 2019c). Service analytics is referred to as a holistic process ranging from data collection to analysis of a service system to provide a value co-creation experience for both customers and providers through service adaptation (Cardoso et al. 2015). With the advent of big data applications and challenges, firms need to develop dynamic service analytics to sense, seize, and transform their service systems through service innovation and adaptation (Teece et al. 2016). Dynamically generated analytical insights allow organizations to cope with environmental dynamism and result in superior performance. Although service analytics has become of strategic importance for service systems, identifying and leveraging the dimensions of service analytics capabilities continues to be a challenge.

Without a clear conceptualization of service analytics capabilities, it would be difficult for firms to plan, invest, and monitor analytics development in a digital marketplace. Motivated by this challenge, the main research question we address is: **what are the dimensions of dynamic service analytics capabilities for service systems in the data-driven digital marketplace?** To answer this research question, we conducted a systematic literature review and 30 in-depth interviews to identify the nature of dynamic service analytic capabilities, and their probable role in enhancing customer engagement, experience and firm performance (Lemon and Verhoef 2016; Ransbotham and Kiron 2018).

2. Literature review

Big data analytics in the data-driven digital marketplace

The word ‘digital economy’ was first coined by Dan Tapscott in his popular book, ‘The Digital Economy: Promise and Peril in the Age of Networked Intelligence’ (Topscott 2015). In essence, digital transformation is not only affecting organizations and governments but also every individual on the planet. The global sales of the e-commerce platform were $2.3 trillion in 2017, and revenues from this sector are expected to reach $4.88 trillion in 2021 (Verhoef 2019). This rapid digitization of the economy also implies that organizations are able to connect with their customers through myriad touchpoints in multiple channels and media, giving rise to a variety of information exchange between service providers and customers, i.e., human-to-machine (H2M), machine-to-human (M2H) and machine-to-machine (M2M) interactions/services (Abbatiello et al. 2017). M2M is also popularly referred to as the ‘Internet of Things’ (IoT). These technological developments and the resulting exchanges are contributing to the data-driven digital marketplace, which includes transaction, video, voice, click-stream, and social media data (Davenport et al. 2012). All these forms of interactions, communications, and exchanges coupled with the shrinking of time slices at which these data are captured, stored, analyzed, and acted upon are contributing to big data and analytics.

In a service economy, BDA can help service providers understand customer experience through their digital footprints (Akter and Wamba 2016). The array of touchpoints, channels, and media are providing critical insights to understand the digital journey for a customer through provider-customer interactions. To better understand the role of service analytics to enhance customer experience, it is necessary to visualize the path a customer takes from beginning to the end of a customer journey (Dremel et al. 2020). For marketing to be effective, it must intervene at the critical junctures that influence their decision making (Court et al. 2009). Lemon and Verhoef (2016) portray the customer journey as a three-stage process consisting of a) pre-purchase, b) purchase, and c) post-purchase phases. As no two customers may interact with the firm in an identical fashion, their '*customer journeys*' may be different, resulting in complex customer-interactions and customer experiences. For example, Google's technologies are getting more sophisticated so that organizations are able to see the links between customers' ad-viewing to the store visit (Ransbotham and Kiron 2018). Similarly, Google's '*store visits*' technology enables an organization to know whether a customer viewed any of its online content prior to a store visit for purchase (Lawson and Srinivasan 2018). Seven-Eleven Japan remained profitable over the last 30 years due to leveraging insights from customer buying patterns, accounting for weather conditions, and sensing and reconfiguring its shelves to suit to local customer needs. It is said that 70% of the products on the shelves are new every year, as these are designed in response to customer preferences (Ross et al. 2013). Analytics enables service providers to leverage customer journey patterns in devising their marketing strategies and respond to customers' needs without waiting for their explicit feedback. It also gives rise to service innovations to optimize customers' experience.

The rise of service systems in the digital marketplace

Due to the emergence of digital platforms, there is a significant growth of data-driven service systems in the form of smart service, mobile service, cloud service, or overall a technology-mediated service (Ferraris et al. 2018b; Lim et al. 2018; Ardito et al. 2019). Services include all activities in which resources (e.g., people, technology) and capabilities (e.g., dynamic, adaptive) co-create value for all the engaged parties (Vargo et al. 2008; Spohrer and Maggilo 2010). Based on the extant literature, we define a service system as a technology-mediated service delivery platform that uses various resources for value co-creation (Polese et al. 2020). In a similar spirit, Maglio and Lim (2016,p.1), define service systems as “configurations of people, information, organizations, and technologies that operate for mutual benefit.” In this digital age, the service system integrates products into the system to create value-in-use since the customers are provided access to goods and services through sharing, such as car sharing (e.g., Zipcar, blablacar), bike sharing (Citi Bike), accomodation (spareroom), luxury fashion sharing (e.g., Bag Borrow or Steal) (Akbar and Hoffmann 2019). Analytics based insights transform a service system by sensing trends/patterns, seizing opportunities and reconfiguring resources under uncertainity (Lim et al. 2015; Opresnik and Taisch 2015; Maglio and Lim 2016).

Service systems categorization

Studying various cases of big data in smart service systems, Maglio and Lim (2016) proposed four categories of innovation in smart service systems. The basis for their categorization is a 2x2 matrix where the x-axis defines the source of BD (i.e., people or objects), and the y-axis depicts where BD is used (i.e., informing people or managing objects). Expanding the notion of providers and consumers beyond humans to encompass autonomous agents, we extend the categorization of Maglio and Lim (2016), as shown in Figure 1. This perspective renders a 2x2 matrix where the x-axis and y-axis represent providers and consumers, respectively. The resulting four quadrants represent the service-encounter domains, which also project that service systems need not be purely autonomous or purely human-centered but can be a combination of them (Motamarri 2018).

Some of the proponents of AI foresee that in the near future, the landscape of the workforce is going to tremendously change as firms may deploy humans and machines (*no-collar workforce*) to work cooperatively in achieving the organizational tasks (Abbatiello et al. 2017).

In Figure 1, the lower-left quadrant denotes the service systems that are completely autonomous. Their presence is already known, the Internet of Things (IOT) are nothing but **agent to agent** interactions, services provided, and are consumed by agents (Bresciani et al. 2018). The upper left quadrant refers to **"machine-to-human service systems"** in which routine services are rendered by machines to humans. The largely prevalent self-service systems like ATMs, self-checkout, etc. belong to this category. The lower right quadrant represents **"human-to-machine service systems"** in which people regularly set the thresholds or define the processes for machines to act on, such as fraud detection or risk assessments for lending by banks. The top right corner represents the conventional "**human-to-human service systems,"** which require customized solutions, such as financial consultancy or medical surgery. The lower left quadrant is the **"machine-to-machine service systems,"** in which structured services are provided from one machine to another machine, such as self-governed turbines and engines. The Internet of Things (IoT) is another example of an agent to agent interactions, in which services are provided and consumed by agents. While service analytics has an important role for the human-centered systems, it has a significantly large value across all the domains. The reason being big data are equally empowering providers, machines, and consumers (Vargo and Lusch 2008) and augmenting their capabilities (Day 1994; Teece 2007) not just at the strategic level but at the operational level across the four quadrants of Figure 1. For example, the growth of IoT is resulting in increased automation, and datafication trend, which is leading to more investment into artificial intelligence (AI) and machine learning (ML) based service systems and relevant analytics (Kumar et al. 2020).

INSERT FIGURE 1 HERE

Service analytics

In analyzing the role of analytics to improve customer engagement, Ransbotham and Kiron (2018 p.4) refer analytics to "The use of data and related business insights developed through applied analytical disciplines (for example, statistical, contextual, quantitative, predictive, cognitive, and other models) to drive fact-based planning, decisions, execution, management, measurement, and learning." Service analytics focuses on analyzing customer's interactions with the providers based on the data captured by the service systems (Fromm et al. 2012; Demirkan and Delen 2013). Wedel and Kannan (2016) synthesize that analytics yields rich benefits that range from information-value to decision-value continuum in marketing. They further decompose the analytics into four levels, namely, a) descriptive, b) diagnostic, c) predictive, and d) prescriptive analytics. Although big data analytics have become an element of strategic importance for service systems, leveraging the insights from service analytics continues to be a formidable task. We define service analytics as to the delivery of insights by leveraging big data analytics for service systems and enable strategic and operational decision making to continuously enhance customer interactivity at every touchpoint and deliver superior customer experience.

Service analytics as dynamic capabilities

BDA may help to build sophisticated future scenarios, but they do not provide the necessary information and knowledge about the future (Teece and Leih 2016). The conventional strategic management approaches of competitive forces (Porter 1980) and strategic conflict (Shapiro 1989) become ineffective in preparing corporations to deal with this level of complexity. Extending the ideas of resource-based theory (Learned et al. 1969; Barney 1991; Leonard-Barton 1992), *dynamic* *capabilities framework* is proposed to enable businesses to determine the best course of action in the face of rapid change and complex settings (Teece et al. 1997; Ambrosini et al. 2009; Barreto 2010). Firms not only need deep and internalized knowledge of products and services, but also need hard-to-imitate capabilities to leverage intellectual assets (Teece 2007). Thus, the fundamental goal of any strategic initiative of a corporation is to achieve a competitive advantage in the market place.

Dynamic capabilities are defined as a "firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. Dynamic capabilities thus reflect "an organization's ability to achieve new and innovative forms of competitive advantage given path dependencies and market positions" (Teece et al. 1997 p.516). In the service industry, dynamic capabilities are particularly relevant as the service providers need to dynamically create, extend, modify, reconfigure and assemble service-elements during service-encounters in response to the customer needs in (near) real-time (Teece 2007).

Dynamic capabilities constitute three broad discrete actions, namely, sensing, seizing, and reconfiguring (Teece 2014). Service providers need to constantly sense the opportunities, direct the organization to seize the opportunity, and continuously reconfigure their assets to achieve strategic success and long-term sustainability. Thus, we define *dynamic service analytics capabilities* (DSAC) as *capabilities that provide the rapid response mechanisms to understand business contexts, visualize possibilities and make decisive actions to enhance business agility and deliver service in (near) real-time*. We also complementarily deduce that organizations need to systematically line up the BDA tools that enable them to sense and seize the opportunity through a dynamic reconfiguration of their assets. It is interesting to note that similar notions are central to the *Information Technology Services Management* (ITSM) standard; and the newer ideas, the *information systems as a service* (Motamarri 2018), emphasize that the primary goal of an information system, i.e., BDA in this case, is to deliver service or value to its users.

3. Research methodology

Drawing on a systematic literature review and in-depth interviews, this study investigates the dimensions of dynamic service analytics capabilities in service systems. The literature review and thematic analysis are conducted following established guidelines (e.g., Tranfield et al. 2003; Akter et al. 2019a). The sources of literature review and in-depth interviews assisted in triangulating the findings (Neuman 2011; Carter et al. 2014). The systematic literature review was supplemented by qualitative interviews for the following reasons. First, big data analytics embraces surveys or experiments in most cases. Surveys are often ineffective in capturing actual behaviors and experiments are beset with capturing the complexity of individuals' behavior in real-life situations. To address these limitations, this study conducted qualitative interviews to unearth the perspectives of managers and practitioners on analytics in service systems, its meanings, settings, structure, and context (Skinner et al. 2000; Silverman 2011).

Review of the literature and thematic analysis

As part of conducting the literature review to understand the role of service analytics capabilities in service systems, three prominent data sources, Scopus, Web of Science (WoS) and Google Scholar have been searched with various key strings to extract relevant extant literature on this subject matter. The keyword search on 'service analytics capabilities' retrieved zero records in both Scopus and WoS, while Google returned three documents that are not relevant. This probably indicates sparse attention to service analytics capabilities in the extant literature. The search strings are service analytics, dynamic service analytics, service analytics culture, big data, big data analytics, big data capabilities, big data analytics capabilities, data analytics, data analytics capabilities, data-driven culture, data-driven decision, data-driven decision making and data-driven services. A summary of the search outcomes is presented in Appendix 1. A total of 321 retrieved articles are screened based in the order of title, abstract, keywords and then the body of the text. Narrowing the list to 40 articles, 17 relevant articles were finally chosen for deeper analysis. The review of these articles has enabled the authors to visualize a multitude of models that tie big data analytics capabilities to measures like firm performance.

Drawing on Braun and Clarke (2006), we used a thematic analysis of the literature review (Ezzy 2002), resulting in a set of 6 themes: *management, technology, talent, data governance, model development, innovation & adaptation capabilities.* These themes were verified by Krippendorff's alpha (or, Kalpha), a reliability measure in content analysis (Krippendorff 2004; 2007). We first estimated the Kalpha by identifying each of the 17 articles under six categories. Second, we applied the procedures of Hayes (2011) and De Swert (2012) to calculate the inter-rater reliability of the six themes (Hayes and Krippendorff 2007). Finally, the findings of the analysis provide a Kalpha value of 0.86, which is well above the threshold level (> 0.80) and give evidence of adequate reliability. The following section reports the findings on the service analytics capability framework using six propositions.

In-depth Interviews and thematic analysis

The study conducted in-depth interviews with analytics professionals of service systems to produce rich findings. Thirty respondents aged between 18-65 were selected for 45-60 minutes' interviews using both convenient and snowball sampling techniques (Saunders et al. 2012). Although most analytics professionals were male, the sample represented diversity in demographics in terms of age, profession, and education, as shown in Appendix 3. To ensure variety and reach a thematic saturation, the sample size of the study was adequate (Kuzel 1999; Guest et al. 2006). The interviews were transcribed, and thematic analysis was again used to identify overarching themes. The statements from the transcribed interviews were the latent manifestations of the themes. Thematic analysis at this phase identifies meanings or threads in interview datasets that continually emerge around six service analytics capabilities (Braun and Clarke 2006). The thematic analysis explores recurrent patterns that identify six capabilities for systematic analysis in the next phase (Braun and Clarke 2006; Fereday and Muir-Cochrane 2006). Figure 2 shows the final six themes/propositions from qualitative interviews, which are consistent with the findings of the literature review, that is, *management, technology, talent, data governance, model development, and service innovation capabilities*.

Triangulation of the findings between the literature review and in-depth interviews

Whereas quantitative methods have statistical or other mechanisms to establish the reliability and validity of research findings, qualitative approaches offer no such possibility (Golafshani 2003). In qualitative research, social scientists adapt the triangulation principles to ascertain the validity of their findings. Depending on the nature of the approach, triangulation in social research may manifest into multiple variations of triangulation, such as method, investigator, theory, methods, measures, data sources (Neuman 2011; Carter et al. 2014). This research is trying to ascertain the findings derived from the literature with in-depth interviews. Thus, this investigation is trying to validate two distinct sources: the literature and interviews. This situation may also mean validating data from two sources, i.e., existing literature and views expressed by individual managers and practitioners. As part of this methodological triangulation, the study complements the literature review with 30 semi-structured in-depth interviews. The interviews assisted in providing various perspectives on service analytics capabilities and also confirm the insights drawn from the thematic analysis of the literature (Golafshani 2003; Neuman 2011; Carter et al. 2014). Triangulation helped in establishing the due rigor and relevance in our findings (Fusch et al. 2018).

4. Findings on dynamic service analytics capabilities

The findings of our review show that service analytics is an emerging research area, and as such there are very sparse publications that deal with the entire gamut of the field (Fromm et al. 2012; Cardoso et al. 2015; Fromm et al. 2016). The authors have not been able to locate any resource specific to service analytics capabilities. Even the specific studies that focused on BDA have conceptualized capabilities under a variety of names like big data analytics capability, business analytics capability, data-driven decision making capability, and marketing analytics (focusing on a specific domain). The extant literature on BDA has the dearth of studies to formulate on what capabilities are required for service analytics for dynamically changing contexts. Our findings from the interviews also support this point.

> *"Currently bigdata is static at the moment; there are not so many agile capabilities for developing models for big data." (Participant # 18, Male 35-40).*

Appendix 2 presents a high-level summary of the dimensions various scholars have investigated. Furthermore, different authors have used different naming for the same capability. Notes accompanying Appendix 2 present the specific name(s) being used by respective scholars. The literature search identified one comprehensive work on the formulation of big data analytics capabilities and its linkage to firm performance (Akter et al. 2016). This model on big data analytics capabilities did not account for business processes, analytic climate, culture, privacy, security, surveillance, and democracy and does not have any specificities pertaining to services. Addressing these gaps in the literature, this paper extends the framework of big data analytics capabilities to the realms of service analytics by fusing the principles of service systems and dynamic capabilities (Cardoso et al. 2015; Maglio et al. 2015; Teece and Leih 2016).

The extant literature treated big data analytics by conceptualizing 13 dimensions, as summarised in Appendix 2. Studies (e.g., Akter et al. 2016; Wamba et al. 2017; Mikalef et al. 2019) have modeled big data analytics capabilities focusing on three major dimensions, such as management, technology, and talent capability. However, this set of analytics capabilities does not provide a comprehensive framework to address the intricacies involved with service systems and especially, does not address variations inherent to service domains (Figure 1). To gain beneficial value from service analytics, service providers need first, to determine their service domain(s); second, to visualize the market and customer requirements; third, to innovate for solutions to address those requirements and finally, to adapt these solutions to the specific needs of customers (agents) through adaptive service models.

INSERT FIGURE 2 HERE

With the increasing concerns about privacy and security of personal data that is being stored, manipulated and shared by organizations beyond the comprehensive abilities of individuals, government bodies like European Union have recently introduced a comprehensive regulation on the use of personal data, termed as *General Data Protection and Regulation* (GDPR). Thus, extending the extant literature on analytics capabilities, we propose to include additional capability dimensions in service analytics: *data governance, model development, and service innovation*. Overall, we identify analytics as dynamic service analytics capabilities consisting of six dimensions, as proposed in Figure 2. We also envisage that DSAC propositions will help a firm establish a competitive advantage in the digital marketplace.

4.1 Management Capability

Management capabilities are reflected in a firm's ability for planning, investment, coordination, and control of service analytics deployments. Planning involves anticipating customer's needs and focusing on appropriate solutions to manage customer demands (Barton and Court 2012). Having identified areas for focus, firms need to invest in cost-effective programs that enable the firm to visualize its planning goals (Manyika et al. 2011). To realize full benefits of service analytics, firms need to facilitate seamless coordination across its functional divisions so as to ensure that all entities share a common vision and based on single truth (Kiron et al. 2014). As organizations become large activities spread across multiple divisions, firms need to focus on control in conjunction with coordination (Davenport 2006). The control ability ensures that firms manage analytics programs within the planned budget, scope, and schedule (PMI 2017), ensuring optimal deployment of resources for the realization of anticipated business outcomes.

Moreover, the management must establish and maintain a data-driven culture in the organization for effective decision making. In various organizations, managers lack knowledge of analytics and are skeptical about it. This knowledge gap needs to be overcome. Management's viewpoint would establish the culture for the rest of the team; therefore, it is important that managers promote a data-driven culture throughout the organization and at all stages, from planning to execution encompassing all decisions in between. In this regard, a participant suggested:

> *"I think culture is one of the most important things in the organization which determines the management's approach to the analytics. There are a lot of top managers that are quite negative toward analytics as they see it as a huge cost and don't see the value of doing so. Therefore, it is important to have good management support for data-driven culture and develop plans in multiple levels". (Participant # 18, Male 35-40)*

The data-driven culture underscores the application of analytics in decision making; however, it does not suggest that all the people have access to all kinds of data. Certainly, data is a sensitive resource that needs to be handled efficiently and very meticulously. If data are accessible to everyone, it bears the risk of inappropriate use and possible violation of any governing laws. One participant commented that:

> *"I don't think data should be available to everyone. I believe the right data should be available to the right people and at the same time." (Participant#21, Male 30-35)*

Overall, respondents identified that management capability to plan, invest, coordinate, and control service analytics projects and outcomes could enhance firm performance.

Proposition 1 *Analytics management capability enhances dynamic service analytics capability.*

4.2 Technology Capability

A service system's technology capability is composed of its infrastructure's connectivity, compatibility, and modularity (Akter et al. 2016). These characteristics enable analytics competency teams to flexibly configure data resources across the functional units to facilitate real-time decision making with a dynamic ability to model business scenarios (Barton & Court, 2012; Davenport, 2012). The technology infrastructure shall connect all of its locations and provide seamless access to service analytics at points of usage. The data resources shall be compatible to work with the decision engines to facilitate decision making. The modularity of the infrastructure enables users to select and formulate models to dynamically manage business situations flexibly, as we derive from a comment of a participant:

> *"A lot of individual digital devices are now being used for capturing data. …Cloud computing is allowing data scientists to access retrospective data… This allows storing and retrieving an unbelievable amount of data from various web services, which have an incredible implication." (Participant#25, Female, 50-55)*

Proposition 2 *Analytics technology capability enhances dynamic service analytics capability.*

4.3 Talent Capability

Talent capability constitutes an important differentiating factor for a service system (Vargo and Lusch 2004). Talent capability consists of management of technology, technical skills, business know-how, and relational knowledge. Matured organizations invest in training and enhancing their employees' analytical skills, thereby creating a competitive advantage. These skills imply that the personnel is capable of executing their job routines in an analytics-driven service system. The findings of the study support the significance of talent capability dimension through the following comments:

> *"Developing talent capability or trying to find the right people for dealing with analytics is the main issue. The large company has resources to train people in big data, but small companies suffer, so the human aspect is very important." (Participant#18, Male 35-40)*

> *"Companies lack skills and tools for data analysis… managers are not aware of big data and how to make a decision with them." (Participant#19, Male 25-30)*

> *"If we are talking about skills, they have to be very good at analyzing numbers, mining data and have skills such as coding, etc." (Participant#20, Male 25-30)*

To derive value from analytics investments, it is not adequate enough for service providers to invest in technology infrastructure, but they also need to invest in skills development of their employees so that employees are able to manage the technology platform. The following comments reflect the importance of talent capability in addition to other capabilities:

> *"I believe the combination of technology and people are vital for valuable results, an organization…need people who understand both technology and people, hence the integration of technology and people are both needed." (Participant#30, Male 40-45)*

> *"Companies need to have the necessary technical capability, but it is the people (talent capability) who can connect the dots among the dataset and have some sort of statistical analytics on the data." (Participant#24, Male 45-50)*

Organizations also need to invest in enhancing the technical skills (Hadoop, Apache, etc.) of their teams so that they can contribute to the other knowledge areas. Apart from technology, firms must train their employees in various business processes and cross-train them where possible to enhance their understanding of the business they support (Davenport et al. 2010). To have an integrative effect on the employee skills, they need to develop skills in communicating and working with other stakeholders, both internal and external (PMI 2017). In this regard, one respondent commented:

> *"… we try to find out what our client's business problem is and how our company can solve those using big data." (Participant # 26, 36-45)*

Proposition 3 *Analytics talent capability enhances dynamic service analytics capability.*

4.4 Data Governance Capability

Systematic management of data over its life cycle; that is, data capture to its organized destruction is essential to derive value from the data assets (Davis and Patterson 2012). Data governance refers to a few specific areas: data architecture, life-cycle management, master data management, and privacy and security management (Wang et al. 2016). The architecture capability enables an organization to identify the requisite data assets, its form, content, and format. Master data management focuses on ensuring the availability, completeness, currency, and accuracy of the stored data sets. While hardware and software appear relatively costlier at the beginning, over a period the organizations' challenge is to invest in data life-cycle management that includes not only capture but their storage and retrieval at the points of demand, ongoing backup and restore as needed, archival for longer-term quality or regulatory needs and systematic erase of data to its end-of-life (Jia et al. 2015). Big data comes with big challenges in terms of access to sensitive and private data of individuals, sometimes inadvertently. Service systems especially, healthcare and financial firms, need to focus on who has access to which data, their continuous business need for it, and how to protect the privacy of individuals (Davis and Patterson 2012; Wang et al. 2016). Security and privacy aspects of individuals go contra to the precision needed to achieve better results from service analytics. Robust service systems also shall focus on the protection of personal data, which is evident in the following comment:

> *"While developing the database, we also look into our service providers' track record and client base to safeguard customers' confidential information and ensure privacy." (Participant #2, Male 46-55)*

Proposition 4 *Data governance capability enhances dynamic service analytics capability.*

4.5 Model Development Capability

Smart service systems like rerouting of traffic, personalization of medicine depend on data and appropriate models. To deliver smart services, firms need accurate and dynamic information about the world and customers (Demirkan et al. 2015). The maturity of BD tools and technologies is enhancing the range of modeling options. To extract value from service analytics, firms need to develop their skills in the development of descriptive, diagnostic, predictive, and prescriptive analytics (Wedel and Kannan 2016). For DSAC to have an impact on a service system's performance, data must flow from its inception to the point of service delivery or every touch-point where a customer interacts with the firm (Vargo and Lusch 2004; Kiron and Shockley 2011; Hall et al. 2016).

Big data essentially consists of a mix of structured and unstructured data, and the processing of the data sets is extremely complex. Reasons being to deliver effective answers to varying business contexts in (near) real-time requires enormous computational abilities and sophisticated algorithms like machine learning or artificial intelligence approaches (Hall et al. 2016). Organizations can build their models via aggregation, sampling, or selection to reduce the dimensionality of big structured data (Wedel and Kannan 2016), as reflected by the following comment:

> *We implement most modern technology and the tools available in the marketplace such as Oracle, SAP, Cognos ReportNet, Business Intelligence other ERP and CRM tools because of their*

integration and the user-friendliness in information generation and application in day-to-day activities…along with a prevalent data-driven culture, and our organization depends on data and a comprehensive set of tools in making customer-related decisions. We monitor and analyze data very critically on a real-time basis of 24 hours. This data is very crucial and critical for a company's performance and approach to the market. (Participant no. 26, Male 46-55)

Descriptive models enable summarization and visualization of data and provide visual cues to organizations to better perceive patterns hidden in BD (Cardoso et al. 2015). Diagnostic models involve identifying variables and their effects through statistical models, thus facilitate hypothesis testing (Cardoso et al. 2015). Predictive models enable firms to forecast future effects of marketing decisions via statistical or simulation techniques (Cardoso et al. 2015; Wedel and Kannan 2016). The complex prescriptive models provide decision making support with possible solution alternatives and their likely business impact (Cardoso et al. 2015; Wedel and Kannan 2016). Wedel and Kannan (2016) suggest that while big data dimensions increase informational value, the increased decisional value comes at the expense of model complexity and processing costs. Firms need to invest in the model development capabilities of their teams and also train all levels of business users to derive value from the insights gained out of service analytics.

Proposition 5 *Analytics model development capability enhances dynamic service analytics capability.*

4.6 Service Innovation Capability

Service innovation may mean the refinement of an existing service or origination of a new service altogether (Maglio and Lim 2016). Organizations in the past are not able to synthesize effectively customer feedback that is beyond their captive systems. However, service analytics capability with its massive capacity to harness data from multiple sources is able to provide deeper insights about the market, competition, and customer's perceptions about their services vis-à-vis competition (Wedel and Kannan 2016). Furthermore, the deeper insights from DSAC provide valuable information about the performance of the service portfolio, value creation, and understanding about unfulfilled/functional failures of services (Petroski 2006; Cardoso et al. 2015; Motamarri 2015). The service analytics is also enabling firms to test various service blueprints prior to their introduction of a new service or enhancement and refine it before formal launch (Bitner et al. 2008).

> *"A good thing about using big data is using customer data to design/redesign customized service mix; for example, few pharmaceutical companies are making personalized medicines." (Participant#17)*

In the evolving service-dominant economies, organizations are switching from product to service orientation (Vargo and Lusch 2004; Opresnik and Taisch 2015). This, in turn, is reflected in the nature of marketing, i.e., 'adaptive selling' to 'service adaptiveness' (Spiro and Weitz 1990; Gwinner et al. 2005; Rust and Huang 2014). The extant literature supports that this service adaptation indeed contributes to improved trust and longevity between buyers and sellers (Cannon and Perreault Jr 1999; Gwinner et al. 2005). Gwinner et al. (2005) point out two important dimensions of service adaptation: 1) adaptive interpersonal behavior (mass customization); 2) service offering adaptive behavior (employee adaptiveness). Wilder et al. (2014) discuss that customers are expecting individual customization in contrast to conventional efficiency drives. Frontline employees' capacity to anticipate customers' feelings, motives, and concerns shall aid in service customization and thus enhance the customer experience. Firms can achieve this by keeping their frontline abreast of the information that enables them to serve the customers better (Wedel and Kannan 2016).

> *"I think our employees have a much better ability to adapt service for individual customers… The employees need to be able to maintain connections, to identify characteristics of their customers, and to do research about the customers that they're coming into contact with. And I think that*

there are many more tools now which are empowering the employees' adaptiveness capability."
(Participant # 03, Male 55-60)

Thus, organizations should invest in developing the capabilities of frontline employees with service analytics skills to yield adaptive services. In essence, evolving a mature service innovation capability shall be a formal goal of service analytics capabilities.

Proposition 6 *Analytics-driven deeper insights generation capability enhances dynamic service analytics capability for service innovation and adaptation.*

5. Discussion and Research Implications

The foregone discussion looked into the service analytics and its pervasive entry into many activities of economic activity. Organizations are increasingly transforming from product-centric to service-centric in the digital marketplace. In recognition of this shift, the authors wanted to explore what has been the role of service analytics in the digital marketplace. It presented an interesting picture of the BDA and the need to transform the analytic insights into capabilities with impetus from the dynamic capabilities framework. Despite the growing interest in big data in the digital marketplace coupled with the size of the services economy, there is an insufficient focus on service analytics research. It is no surprise that Ostrom et al. (2015) have identified big data in services as one of the 12 service research priorities. Towards advancing service analytics research, it is further established that there is a large gap between the importance of big data for science and its know-how (Ostrom et al. 2015).

Theoretically, to address the research gap of service analytics capabilities in the digital marketplace, we took an exploratory methodological approach to investigate its dimensions by applying a systematic literature review and in-depth interviews (n=30) of practitioners and scholars. Our framework presents six propositions that enable the building of DSAC in the data-driven marketplace. Our findings on management, technology, talent, data governance, model development, and service innovation capability contribute to the dynamic capabilities literature. For example, the digital marketplace is currently inundated with data, and building *data governance capability* is essential for service firms to quickly identify trends in volatile and uncertain environments. In addition, our findings show that firms that are better equipped with the strategic *management* of their *talent and technology* capabilities can better seize an opportunity in the digital marketplace. Our findings also resonate with the fact that *model development and innovation capabilities* bring the necessary transformation capability and strategic agility to avoid disruptive threats in the fast-changing digital marketplace (Warner and Wäger 2019). In the service organization's overall portfolio of capabilities, we argue DSAC as the second-order dynamic capabilities that constitute astute strategic thinking to sense an unmet service need, seize the emerging opportunity and develop the best resource configuration for the present and future digital marketplaces (Teece 2018b).

Practically, our proposed DSAC framework contributes to the following 12 stages of the service life cycle (SLC) (Motamarri 2015) with solid insights for decision making: 1) perceived market/customer needs; 2) perceived service opportunity/innovation; 3) service design; 4) servicescape/technology (touchpoints); 5) service encounters; 6) service fulfillment; 7) service experience; 8) service quality; 9) voice of the customers; 10) service demand; 11) service refinement and 12) service retirement. The findings of the study resonate with the role of DSAC across the SLC to reshape competitive advantage in the digital marketplace, as presented in Table 1. Combining these discussions on the DSAC dimensions, SLC, and digital marketplace research opportunity, we propose a future research agenda as detailed in Table 2. The enumeration also details the DSAC dimension, sub-dimensions, and relevant research questions. For example, aligned with Vidgen et al. (2020), our future research agenda on data governance urges to investigate five principles (utility, rights, justice, the common good, and virtue) to investigate the ethical implications of analytics on the stakeholders. Similarly, the study has identified the research agenda for all other service analytics areas in Table 2. Although the study has proposed six dimensions for the DSAC, the dimensions are quite inter-related and integrated as reflected in the following comment:

> *…when our company started their big data journey the biggest issue they faced, which is still faced by many other organizations, that there are many big data providers out there, which only focuses on technology. It was a major drawback for our company when they first started the journey. However, the biggest issue is the skill set we have, we don't have a shortage of data scientists or engineers, but the biggest gap is the difference between managing data and business application or associating the data toward a business problem. But now we have both types of people who are good at data management and business application. We prioritize those talent capabilities who have insight into the linkage between data management and application.* (Participant#26, Male)

INSERT TABLE 1 & TABLE 2 HERE

6. Conclusions

Reflecting on the role of digitization on organizational processes and the explosive growth of data, this research explored the role of dynamic service analytics capabilities. A systematic search of the extant literature is performed to deduce insights. There has been little work on service analytics, and there is a significant gap in the literature to address the research question, "What are the dimensions of (dynamic) service analytics capabilities (DSAC)?" Synthesizing literature on service systems, BDA, and dynamic capabilities, we propose a DSAC framework and elaborate on six propositions. We have also discussed the role of DSAC across the service life cycle. The dimensions of the DSAC framework is needed for service systems to manage environmental dynamism brought upon by big data. Service systems shall continuously focus on developing dynamic analytics capabilities to adapt, orchestrate, and innovate amidst rapid market and technological changes (Teece 2014). Thus, this paper presents a useful starting point for research on dynamic service analytics capabilities for service systems in the digital marketplace with a mapped agenda for future research.

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Figures

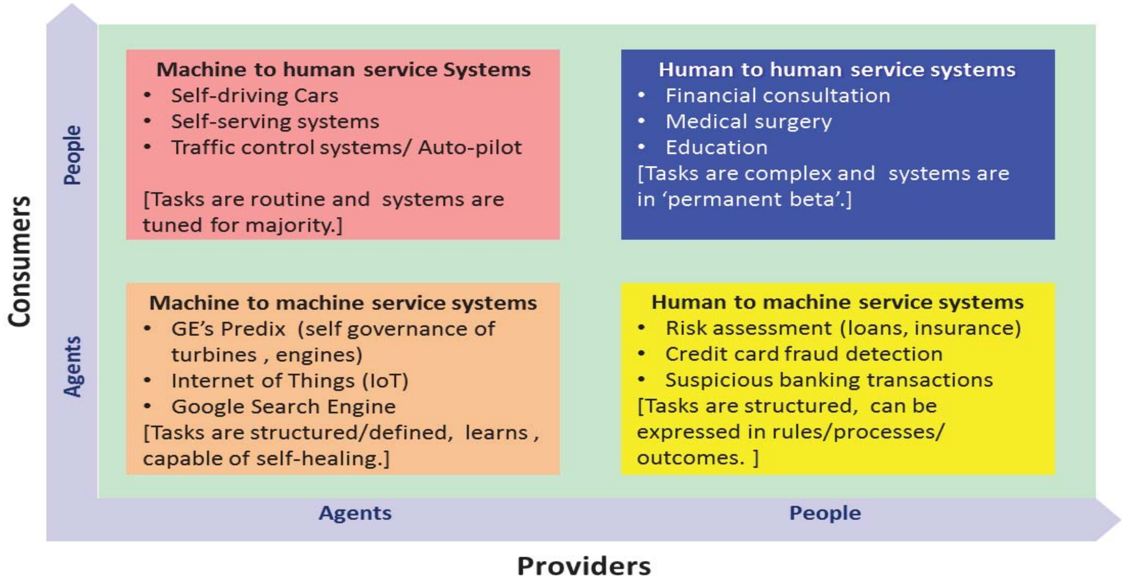

Figure 1: Service Systems Categorisation

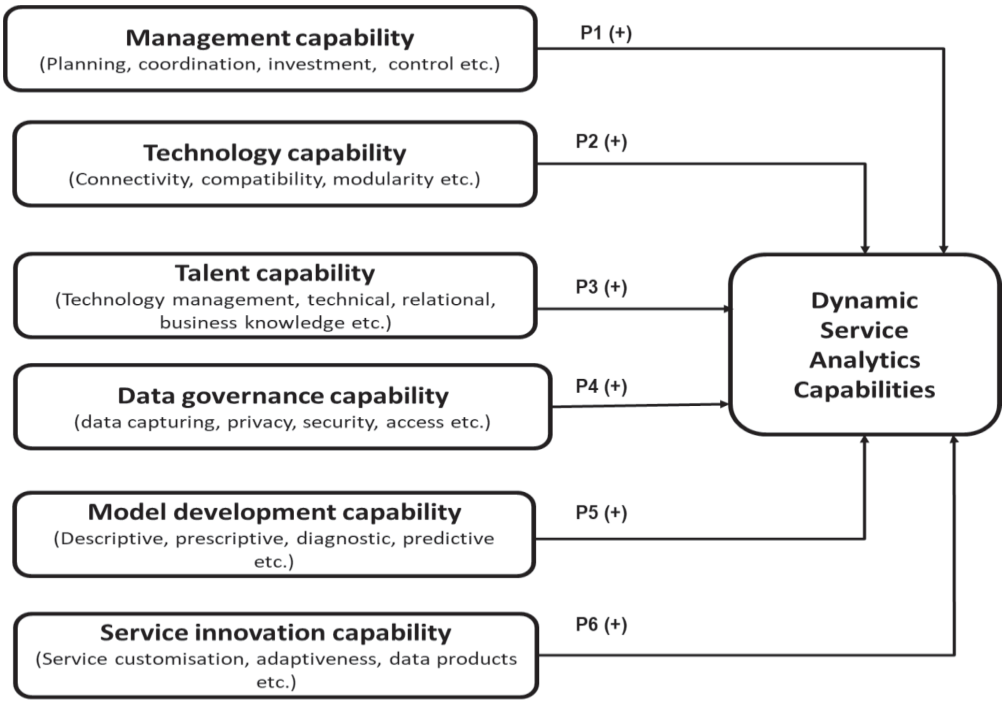

Figure 2: Dynamic Service Analytics Capability Framework

Table 1: Role of Dynamic Service Analytic Capabilities across the Service Life Cycle

Stage	Service Life Cycle (SLC)	Analytics Opportunities	Sources
1	Market needs	DSAC provides insights on market needs, customer feedback and trends.	(Lawson and Srinivasan 2018)
2	Service innovation	Innovate for solutions for the identified needs.	(Chesbrough 2011; Oliveira and von Hippel 2011; Davenport and Kudyba 2016)
3	Service design	Harness internal/external success/failure stories to design services that meet/exceed customer needs.	(Hauser and Clausing 1988)
4	Servicescape/ Touchpoints	Assess success/failure of technology/touchpoints and devise effective channels.	(Lemon and Verhoef 2016; Lawson and Srinivasan 2018)
5	Service encounters	DSAC to provide customer buying behaviors, market performance, competition.	(Lemon and Verhoef 2016; Lawson and Srinivasan 2018)
6	Service fulfillment	DSAC to provide fulfillment insights and customer perceptions.	(Lemon and Verhoef 2016; Lawson and Srinivasan 2018)
7	Service experience	DSAC to provide customer experience vis-à-vis market and competition.	(Lemon and Verhoef 2016; Lawson and Srinivasan 2018)
8	Service quality	DSAC to provide customer service quality perceptions and areas for improvement.	(Parasuraman et al. 1988; Lemon and Verhoef 2016)
9	Voice of the customers	DSAC to provide insights on customer pain points, hurdles for service demand, opportunities for improvement.	(Griffin and Hauser 1993; Ross et al. 2013)
10	Service demand	DSAC to provide insights on market size, competition, market share, demand patterns.	(Ross et al. 2013)
11	Service refinement	DSAC insights to guide service refinement.	(Ross et al. 2013; Davenport and Kudyba 2016)
12	Service retirement	DSAC insights to guide strategic decisions to retire existing services.	(Motamarri 2015)

Table 2: Dimensions, sub-dimensions and research questions for dynamic service analytics capabilities

Dimensions	Sub-dimensions	Research questions	Sources
Management capability	Planning, Investment, Coordination, Control	How can organizations systematically identify opportunities for DSAC? What value conceptualizations help in evaluating the outcomes of DSAC investments? How organizations can orchestrate DSAC to enhance organizational agility and performance?	(Khalifa 2004; Marsella et al. 2005; Davenport 2006; Kiron et al. 2014; Akter et al. 2016; Maglio and Lim 2016; Wedel and Kannan 2016; Mikalef et al. 2017; PMI 2017)
Technology capability	Connectivity, Compatibility, Modularity	How to integrate services data from external and internal sources to gain insights? How can smart technologies enhance socio-technical interactions with service systems?	(Barton and Court 2012; Davenport 2012; Demirkan et al. 2015; Akter et al. 2016; Maglio and Lim 2016)
Talent capability	Technology management, Technical knowledge, Business knowledge, Relational knowledge	What are the impacts of the continual outsourcing of technology to outside firms? How to train a workforce in a continually changing technological context?	(Davenport et al. 2010; Akter et al. 2016)
Data governance capability	Data architecture, Life-cycle management, Master-data management, Privacy, and security management	What standards are needed to systematically manage the life cycle of service data? Does DSAC alter the definitions of security, privacy & ethics? What frameworks are needed for firms to benchmark their master data management practices?	(Demirkan and Delen 2013; Ransbotham et al. 2015b; Wang et al. 2018)
Model development capability	Descriptive, Diagnostic, Predictive and Prescriptive models	What frameworks are needed to map information value versus decision value across business functions? How can firms empower their employees with a modeling dashboard? How can firms leverage dynamic models in enhancing service delivery?	(Cardoso et al. 2015; Wedel and Kannan 2016; Mikalef et al. 2020)
Service innovation & adaptiveness capability	Service adaptiveness, Service refinement, New service development	Does DSAC enhance service adaptiveness? If so, what factors mediate the relationship? How firms institutionalize service innovation through DSAC?	(Marsella et al. 2005; Wilder et al. 2014; Cardoso et al. 2015; Maglio and Lim 2016; Wedel and Kannan 2016; Mikalef et al. 2017)

Appendix 1: Summary of Literature Search

Search Theme			Service Analytics/ BDA Capabilities			
Search #	**Date**	**Level**	**Search String**	**Database**	**Results**	**Useful**
1	21-Aug-17		Service Analytics Capabilities	Scopus	0	
2	21-Aug-17		Service Analytics	Scopus	34	
	21-Aug-17	2.1	- Capabilities	Scopus	4	
	21-Aug-17	2,2	- Culture	Scopus	1	No
	29-Aug-17		Service Analytics	Google	1,020	
	30-Aug-17		Service Analytics	Google	42	No
	30-Aug-17		Service Analytics Capabilities	Google	3	No
	30-Aug-17		Service Analytics	WoS	18	No
	30-Aug-17		Service Analytic(s) Capabilities	WoS	0	
3	21-Aug-17		Service Analytics Culture	Scopus	1	No
			Service Analytics Culture	Google	1	No
			Service Analytics Culture	Google	0	
4	21-Aug-17		Big Data	Scopus	34,111	
	21-Aug-17	4.1	- Analytics	Scopus	9,773	
	21-Aug-17	4.1.1	- - Capabilities	Scopus	1,178	
	21-Aug-17	4.2	- Capabilities	Scopus	2,628	
5	21-Aug-17		Big Data Capabilities	Scopus	26	
6	21-Aug-17		Big Data Analytics Capabilities	Scopus	18	
	30-Aug-17		Big Data	WoS	19,200	
			- Analytics	WoS	3,346	
			- Analytics Capabilities	WoS	15	2
			Big Data Analytic? Capabilities	WoS	4	0
7	21-Aug-17		Data Analytics	Scopus	5,771	
		7.1	- Capabilities	Scopus	687	
	30-Aug-17		Data Analytic?	WoS	3,496	
	30-Aug-17		Data Analytic? Capabilities	WoS	15	1
	4-Sep-17		Analytics Capabilities	Google	2,820	18
	5-Sep-17		Analytics Capabilities	Scopus	120	
	11-Sep-17		Analytics Capabilities	WoS	51	
8	21-Aug-17		Data Driven Culture	Scopus	11	
9	28-Aug-17		Data Driven	Scopus	28,861	
		8.1	- Culture	Scopus	1,060	
		8.1	- Decision Making	Scopus	2,584	
		8.1	- Services	Scopus	4,812	
	30-Aug-17		Data Driven	WoS	20,342	
	30-Aug-17		- Culture	WoS	158	
	30-Aug-17		- Decision Making	WoS	809	
	30-Aug-17		Data Driven Culture	WoS	2	0
	30-Aug-17		Data Driven Decision	WoS	319	
	30-Aug-17		Data Driven Decion Making	WoS	211	
10	28-Aug-17		Data Driven Services	Scopus	39	2
	30-Aug-17		Data Driven Services	WoS	13	1

Appendix 2: Dimensions of Big Data Analytics

Dimension	Big Data Analytics Capability	Business Analytics Capability	Data-Driven Decision Making Capability
Management Capability	(Akter et al. 2016) (Mikalef et al. 2019) (Gupta and George 2016)		
Technology Capability	(Akter et al. 2016) (Gupta and George 2016)	(Cosic et al. 2015)	
Talent Capability	(Akter et al. 2016) (Gupta and George 2016)[d]	(Cosic et al. 2015)[a1]	
Data Governance Capability	Akter et al. (2019a) Mikalef et al. (2019)	(Cosic et al. 2015)	(Jia et al. 2015)
Data Analytics Capability			(Jia et al. 2015)
Insight Exploitation Capability			(Jia et al. 2015)
Performance Management Capability			(Jia et al. 2015)
Integration Capability			(Jia et al. 2015)
Culture Capability	(Gupta and George 2016)[e]	(Cosic et al. 2015)	
Investment Capability	Akter et al. (2019b)		
Linkage Capability	Akter et al. (2019a)		
Data Capability	(Gupta and George 2016)		
Intensity of Organisational Learning	(Gupta and George 2016)		

Notes:
[a1, a2]: People Capability; Personnel Capability
[b]: Infrastructure Capability
[c]: Relational Network Capability
[d]: Technical skills
[e]: Data Driven Culture

Appendix 3: demographic profile of the respondents

Demographic Characteristic	Sub-Level	Count n=30	(%)
Gender	Male	17	57%
	Female	13	43%
Profession	Customer Relationship Manager	2	7%
	Top Executive	1	3%
	Academic scholars	8	27%
	Middle manager in IT	1	3%
	New business development manager	1	3%
	Customer value chain manager	1	3%
	Top data analytics managers	2	7%
	Middle manager in healthcare	1	3%
	Service analysts in big data environment	3	10%
	Services Manager	1	3%
	Logistics Officer	1	3%
	Search engine manager	1	3%
	IT support manager	1	3%
	Service blueprint designer	1	3%
	B2B service banking manager	1	3%
	Service researcher	3	10%
	Retail	1	3%
Education	Bachelor	10	33
	Masters	15	50
	Research degree	5	17
Age	26-35	8	27
	36-45	10	33
	46-55	9	30
	>55	3	10