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Reshaping Competitive Advantages with Analytics Capabilities in Service Systems

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Abstract

Big data analytics capability can reshape competitive advantages for a service system. However, little is known about how to develop and operationalize a service system analytics capability (SSAC) model. Drawing on the resource based view (RBV), dynamic capability theory (DCT) and the emerging literature on big data analytics, this study develops and validates an SSAC model and frames its impact on competitive advantages using 251 survey data from service systems analytics managers in the U.S. Partial Least Squares (PLS)-Structural Equation Modeling (SEM) was used as a data analysis technique to develop and validate the hierarchical SSAC model. The main findings illuminate the varying importance of three primary dimensions (i.e., service system analytics management capability, technology capability and personnel capability) and various respective subdimensions (i.e., service system planning, investment, coordination, control, connectivity, compatibility, modularity, technology management knowledge, technical knowledge, business knowledge and relationship knowledge) in developing overall analytics capabilities for a service system. The findings also confirm the strong mediating effects of three dynamic capabilities (i.e., market sensing, seizing and reconfiguring) in establishing competitive advantages. We critically discuss the implications of our findings for theory, methods and practice with limitations and future research directions.

Keywords: Big data, service analytics capability, dynamic capability, competitive advantage.

Article Classification: Research paper

1.0 Introduction

Stories abound about service firms applying big data analytics (BDA) and achieving competitive advantages. BDA is now identified as the new oil, the new soil, the next big thing, and the force behind a new management revolution (Davenport & Harris, 2017; Duan, Cao, & Edwards, 2018; Dubey et al., 2019; McAfee & Brynjolfsson, 2012; Ransbotham, Kiron, & Prentice, 2016; Wang, Gunasekaran, Ngai, & Papadopoulos, 2016; Zhan & Tan, 2018). International Data Corporation (2019) has predicted that BDA industry is going to achieve US$274.3 billion revenues by 2022 with more than half of it from the service sector, including IT ($77.5 billion) and business services ($20.7 billion). In a similar spirit, Organization for Economic Cooperation and Development (OECD, 2020) states, "Data-driven innovation forms a key pillar in 21st-century sources of growth. . . large data sets are becoming a core asset in the economy, fostering new industries, processes, and products and creating significant competitive advantages". Indeed, BDA has reshaped competitive advantages for various service systems, such as movie streaming platform Netflix has grown from $5 million in revenues in 1999 to $20 billion in 2019 through its advanced analytics capability (Davenport & Harris, 2017; Watson, 2020). Similarly, Amazon web services (AWS), the fastest-growing cloud platform, made $26 billion worth of sales in 2018 through its data storage, advanced analytics and recommendation engines (Page, 2019).

Despite various success stories, the ever-increasing number of service systems across the world grapple with big data and struggle how to use robust analytics capabilities to enhance competitive edge (Ransbotham & Kiron, 2017). According to Davenport and Harris (2017, p.2538) "The overwhelming majority of organizations, however, have neither a finely honed analytical capability nor a detailed plan to develop one". Specifically, little is known about how to develop and operationalize service system analytics capability (SSAC) and model their effects on outcome constructs. As a result, analytics is losing its lustre though there is a massive amount of data, better technology and continued top management attention to the field (Ransbotham et al., 2016). In the backdrop of this problem, our research puts forward two research questions: **(i) what are the building blocks of SSAC (ii) to what extent the contribution of SSAC to competitive advantages are mediated by dynamic capabilities, that is market sensing, seizing and reconfiguring?**

Services are becoming the dominant form of economic exchange worldwide (Fitzsimmons, Fitzsimmons, & Bordolai, 2014; Spohrer & Maglio, 2008). Maglio and Lim (2016) define service systems as "configurations of people, information, organisations, and technologies that operate for mutual benefit" (p.1). Information derived from big data turns service systems smarter by facilitating learning, dynamic adaptation and decision making under uncertainty (Lim, Kim, Heo, & Kim, 2015; Maglio & Lim, 2016; Medina-Borja, 2015; Opresnik & Taisch, 2015). We define service system analytics as to the process of capturing, and analysing the data generated from the execution of a service system to improve, extend, and personalize service to create value for both providers and customers (Cardoso, Hoxha, & Fromm, 2015). The study puts forward the service systems analytics capability (SSAC) model combining three key dimensions: technology, management and personnel capability.

Our study makes two significant contributions to the emerging data-driven service systems research. The first is proposing SSAC as a higher-order enabler of DCs, which consists of three dimensions and eleven sub-dimensions. Although service systems analytics using big data have been frequently identified as a research priority area in information systems (Agarwal, Shroff, & Malhotra, 2013; Agarwal & Dhar, 2014; Goes, 2014) and operations (Opresnik & Taisch, 2015; Sheng, Amankwah-Amoah, & Wang, 2017; Tan, Zhan, Ji, Ye, & Chang, 2015; Zhong, Newman, Huang, & Lan, 2016), there are few studies which have developed an SSAC model and assessed the importance of its dimensions and sub-dimensions. The second is extending the significance of three dynamic capabilities (i.e., market sensing, seizing and reconfiguring) as full mediators between higher-order SSAC and competitive advantages, which address the research call by Teece and Leih (2016) on how to address uncertainty in a big data environment. This implies that analytics might not gain a competitive edge if it fails to achieve adequate dynamism in ever-changing service systems environments.

2.0 Literature Review and Theories

2.1 Resource-based view (RBV) and Dynamic Capabilities (DC)

The theory of resource based view (RBV) is rooted in that argument that firms that possess various resources can achieve competitive advantage (Barney, 1991; Helfat & Peteraf, 2009). The building blocks of the theory are built on the VRIO framework, which indicates valuable, rare, imperfectly imitable and organization of resources can leverage their full competitive potential (Barney & Clark, 2007). Indeed, the theory works on two principles: resource heterogeneity (i.e., development of unique resources to perform a certain function) and resource immobility (i.e., synergistic benefits from unique resources) to continue its sustainable advantage (Barney & Hesterly, 2012). Although resources and capabilities are the basic components of RBV, it is important to distinguish between these two concepts. Whereas resources are tangible and intangible assets (e.g., technology, personnel and management), capabilities are processes that utilize resources into performance (Makadok, 1999). According to RBV, the productivity of a firm depends on its capability to manage its unique resources (Morgan, Slotegraaf, & Vorhies, 2009).

Although DC perspective is considered to be founded on the resource-based view (RBV) of the firm, Teece, Pisano, and Shuen (1997) made every attempt to differentiate them from the static orientation of RBV. Whereas RBV focuses on current resources (both tangible & intangible) and operational capabilities, DC focuses on meaningful modification of its current resource base. Teece et al. (1997) have proposed DC as a means of potentially overcoming some of the weaknesses of the RBV by renewing and reconfiguring assets and capabilities of the firm to ensure that they continue to provide benefits and competitive advantage. Dynamic capabilities (DCs) are regarded as higher-level capabilities that organize a firm's resources to develop and sustain competitive advantage and eventually performance, particularly in a changing environment (Barreto, 2010; Teece, 2014; Zollo, Cennamo, Neumann, & Environment, 2013). The ordinary capabilities of a firm are concerned about doing things right; however, DCs are different as they enable a firm to direct its ordinary capabilities toward high-payoff activities which ensure that the firm's resources can accommodate rapidly shifting global service environments (Helfat & Peteraf, 2015; Teece, 2014).

Dynamic capabilities (DCs) arguably have gained momentum because they show a path to competitive advantage during changing environment (Helfat & Peteraf, 2009; Zollo, Bettinazzi, Neumann, & Snoeren, 2016; Zollo & Winter, 2002). Using the Schumpeterian logic of creative destruction, DC view has emerged has a strong theoretical foundation in strategic management and other reference disciplines to sense and seize opportunities (e.g., technological) and transform value chain to develop a strategic fit between its capabilities and changing market opportunities. They typically refer to a subset of organizational capabilities that can make a change in the existing resource base and support systems, its ecosystem and relevant environmental factors and overall strategy (Schilke, Hu, & Helfat, 2018).

Despite varying propositions of DC perspective since its inception, there is growing consensus on the idea that DCs are deliberately constructed and refer to a set of distinctive, repetitious and highly patterned routines. The growing importance of DC perspective is driven by the fact that it can make a systematic change through the renewal of operational capabilities and ability to respond to the change in the market. The DC perspective ensures strategic change primarily by its three activities: sensing opportunities and threats in the macro-environment through an environmental scanning, seizing opportunities through a solid business model, which significantly influences business value and firm performance and finally transforming existing business function and relevant strategies through continuous alignment and realignment of both tangible and intangible resources.

In dynamic environments, firms need to reconfigure their resources to accommodate changing needs to achieve service innovation (Kim, Song and Triche 2015) and maintain competitive advantages (Ambrosini, Bowman and Collier 2009; Kozlenkova et al. 2014; Wu 2010). To sustain competitive advantage and succeed in developing robust analytics platform, the DC supplements the RBV by identifying, integrating, reconfiguring, gaining and releasing resources to cope effectively with changing circumstances and achieve new resource configurations as their markets advance (Ambrosini, Bowman, & Collier, 2009). While prior research has investigated the enablers, antecedents and outcomes of DC, there is no research as of now which investigates the impact of services systems analytics capabilities as resources that contribute to dynamic capabilities.

2.2 Service System Analytics Capabilities

Analytics capabilities play a pivotal role in helping service systems develop dynamic capabilities for where the organization currently is and where it is heading to (Krishnamoorthi and Mathew 2015). Adoption of big data and advanced analytics have become a decisive competitive asset in many industries to improve analytics capabilities (Popovič, Hackney, Tassabehji, & Castelli, 2018). SSAC helps firms identify data-based insights to improve decision-making effectiveness through its direct contribution to sensing, seizing and transforming and indirect contribution to overall performance (Kiron, Prentice, & Ferguson, 2014a, 2014b; Ransbotham & Kiron, 2017; Ransbotham et al., 2016).

This study argues that SSAC enables dynamic capabilities to facilitate the continuous generation of solid insights for better decision making. The extant literature shows that there are three key analytics resources—technology, management and people at the core of SSAC. Service system management capability represents the ability to manage BDA across core business and operations functions (i.e. big data management). Personnel capability indicates the skill or knowledge that data scientists or service analysts should possess. Technology capability indicates the availability of advanced IT infrastructure capability (e.g., IT infrastructure enabling open-source platforms such as cloud-based computing). Understandably, the components of SSAC provide key insights which enable the firm to align required resources with business strategies, develop reliable and cost-efficient systems and anticipating IT needs, develop necessary applications, facilitate information-sharing across business units, and make it easy to develop common systems integrating various organizational functions (Akter & Wamba, 2016). A service system can gain an advantage over its competitors through analytics capabilities. Because, it will be difficult to understand and imitate this combination of capabilities and to combine insights and apply them in conjunction with other complementary resources (Teece, 2014).

In the current big data environment, researcher, practitioners and analytics professionals suggest capitalizing on analytics-driven DCs to achieve competitive advantage in the market. Service systems that are operating in such a dynamic big data environment need to focus on developing strong analytic resources to adapt and innovate with market and technology developments (Teece, 2014). SSAC can play a key role in providing quick responses to mission-critical applications in information-intensive environments by allowing the firms to create, extend and modify their tactics to ensure their survival in fast-changing environments (Eisenhardt & Martin, 2000).

In order to generate the firm-level DCs, Teece et al. (1997) argued that an organization should encourage the coordination of a particular set of underlying processes and components, such as sensing, seizing and reconfiguring. Sensing refers to the identification, development, codevelopment, and assessment of big data opportunities in relation to customer needs. Seizing refers to the mobilization of resources to address needs and opportunities and to capture value from doing so. Reconfiguring refers to the continued renewal and taking advantage of emerging big data opportunities and reconfiguring fundamental capabilities (Teece, 2014). However, despite a significant stream of research into how big data and firm performance, we have very limited knowledge in how service systems can align their resources with DCs to adapt changes in their business environment (Fischer, Gebauer, Gregory, Ren, & Fleisch, 2010).

The theory of competitive advantage suggests that it is essential to develop and capitalize on a firm's resources to gain a competitive positional advantage (Day, 1994; Porter, 2008). SSAC provides the impetus to develop and use resources and dynamic capabilities, which would eventually enhance the competitive advantage. As such, the logical relationship between SSAC, dynamic capabilities and competitive advantage (Figure 2), can be precisely captured if they are considered simultaneously (Day & Moorman, 2010).

2.3 Qualitative study: Identification of the dimensions of SSAC

As part of qualitative investigation, we applied both a systematic review and Delphi study to answer our research question on identifying the dimensions and subdimensions of SSAC. We applied multi-method approaches so that we can "compensate for the flaws, and leverage the strengths, of the various available methodologies" (Mangan, Lalwani, & Gardner, 2004,p.569). As such, the systematic review helps us to explore a broad literature to identify the themes and subthemes of SSAC and Delphi study contributes to identify and sort the dimensions and their subdimensions.

Systematic literature review:

Following the guidelines of Akter and Wamba (2016) and Thomas and Leiponen (2016) in BDA research and Benedettini and Neely (2012) in services research and Tranfield, Denyer, and Smart (2003) in management research, we conducted a systematic review to establish rigor in identifying the dimensions of SSAC (see Figure 1). A systematic literature review is a useful process to gather practical and concrete evidence on the themes of our enquiry. Based on the thematic analysis guidelines provided by Braun and Clarke (2006), we explored the extant literature, and the findings provided us three significant themes of SSAC: management, technology and personnel capabilities with various subdimensions under each theme. Figure 1 shows the research protocol encapsulating search strategy and publication selection criteria to address our research question.

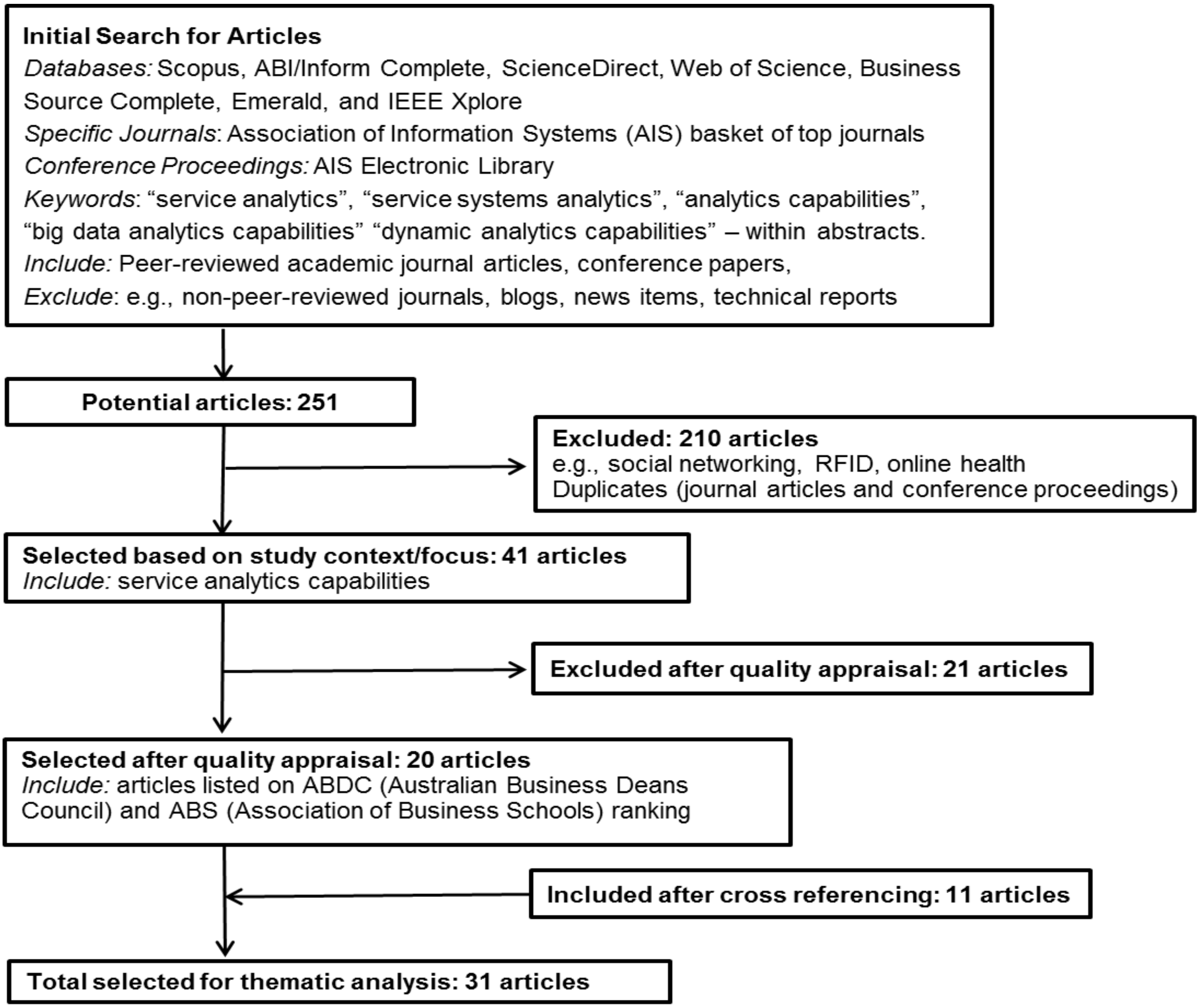

Figure 1 Article search and selection process

Delphi studies:

Using Delphi method, we used experts opinions to solve our research problem by reaching a consensus through a combination of qualitative and quantitative techniques (Bourgeois, Pugmire, Stevenson, Swanson, & Swanson, 2006). This method allows to sort and rank analytics capability dimensions in service organisations in order to develop an SSAC model. We conducted the first round of the Delphi study in December 2016 (n=20) and the second round in April 2017 (n=15) with respondents that represent a balance of analytics practitioners, consultants and academics. The first round focuses on brainstorming to identify and confirm technology, management and personnel capabilities as the three primary dimensions of SSAC. In the second round, we asked experts to list subdimensions under each primary dimension and identify their relative importance. The Delphi findings also confirm that development of SSAC can help build dynamic capabilities to establish competitive advantages. We selected at least 18 years old participants based on whether they have analytics experiences of minimum of three years. Using personal contacts and snowball sampling, we ensured diversity in samples in terms of gender, education and industry types (see Table 1).

Table 1

Descriptive statistics of the Delphi sample.

	Percentage		**Percentage**
Age (years)		**Gender**	
18-24	21	Male	78
25-34	27	Female	22
35-44	28	**Education**	
45-54	14	HSC	8
55 above	10	Degree	43
		Postgraduate Degree	51
Analytics experience			
1-3 years	50	**Industry**	

4-10 years	38	Education	12
More than 10 years	12	Banking	25
		Insurance	11
		Retail Professional	19
		ICT	27
		Others	6

2.4 Conceptual Model and Hypotheses

Based on the findings of the literature review and two Delphi studies, this study proposes a higher-order SSAC model, which consists of three major dimensions (i.e., management, technology and personnel capabilities) and eleven sub-dimensions (see Figure 2).

Theoretically, we argue that the third-order SSAC (e.g., service system analytics capability) operates on both the firm's second-order (e.g., service analytics management capability, technology capability and personnel capability) and first-order, fundamental resources (i.e., planning, investment, coordination, control etc.). Whereas the first-order resources refer to basic organizational resource base, the second-order resource reflects them as a whole. Consequently, SSAC is the highest-order capability, which is founded on developing a valuable and varied resource base for developing DCs in the changing big data environment. This paper argues that this distinction between SSAC and DC enhances theoretical precision to clarify how organizational routines are intertwined to form SSAC and facilitate DC. In particular, there is a paucity of an empirical study examining the role of higher-order RBV that facilitates sensing, seizing and reconfiguring for achieving competitive advantage. As such, the proposed model aims to address this gap in two ways. First, we explore the dimensions SSAC as an enabler of DC in a big data environment. Second, we investigate the mediating roles of DCs between higher-order SSAC and firm performance.

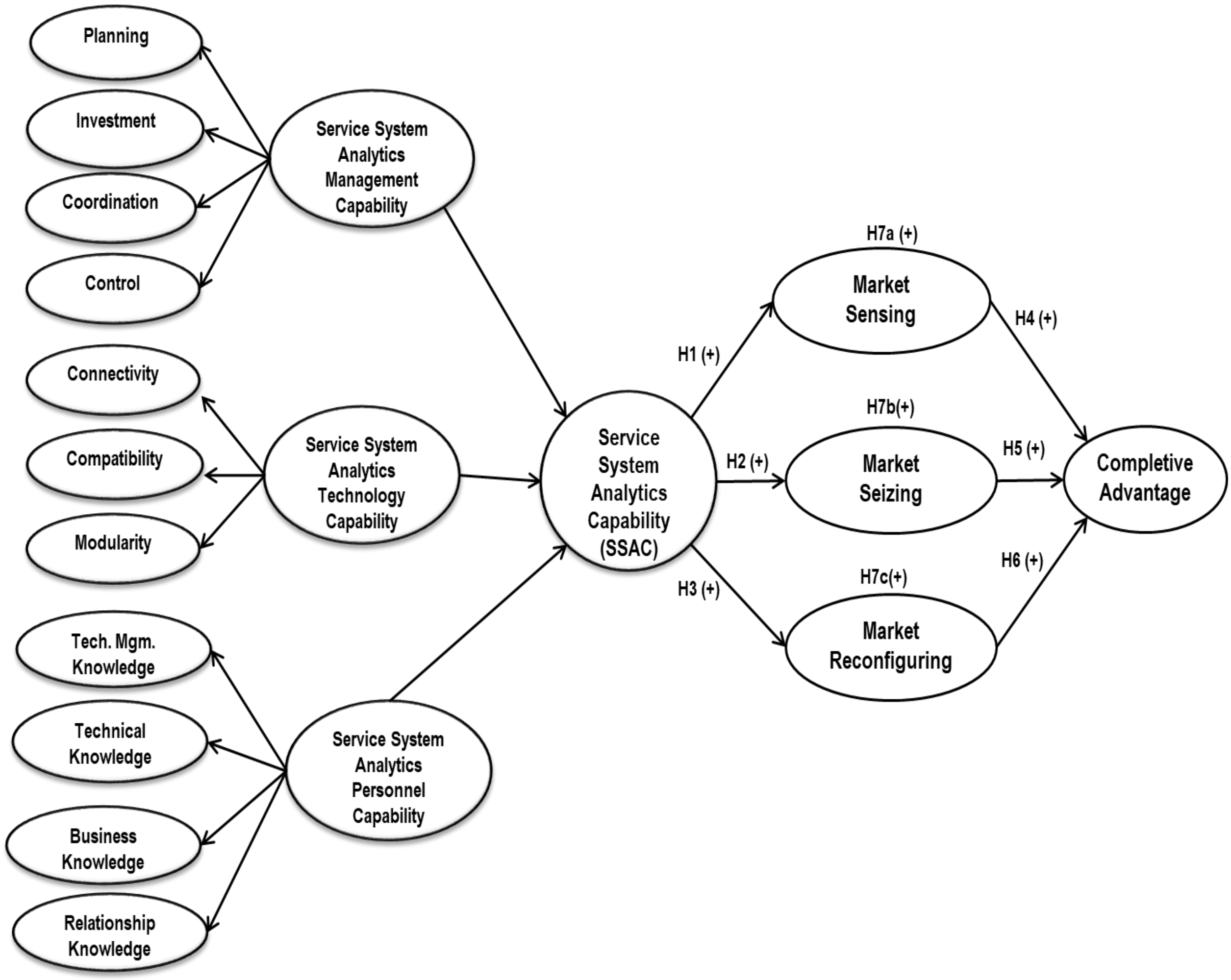

Figure 2: Research Model

2.4.1 The impact of SSAC on sensing, seizing and reconfiguring

SSAC helps a service firm to develop DCs to adapt to any extraordinary or unusual phenomenon and take advantage of opportunities created. Service systems develop analytics-based solutions, which play an instrumental role to sense, seize and transform opportunities (Kaisler, Armour, Espinosa, & Money, 2013). In the current age of data rich environments, access to and use of big data analytics is a strong prerequisite for developing DCs to discover opportunities (Teece, 2018).

SSAC builds the antennae for DCs to detect the weak signals about the changing environment in times of ambiguity and uncertainty, as data provide various insights and clues (Barreto, 2010; Helfat & Peteraf, 2015; Peteraf, Di Stefano, & Verona, 2013). In order to capitalize the sensed and seized service opportunities, the firm needs to reconfigure or transform its capabilities (Inigo, Albareda, Ritala, & Innovation, 2017; Inigo, Albareda, & Change, 2019). SSAC would enable the firms to achieve dynamic capabilities by aligning internal processes and routines (Chesbrough, 2010; Zollo et al., 2016). For example, SSAC support market sensing activities by exploring market trends, developing technological sophistication and managing skills of people. Similarly, SSAC provides a key insight to reconfigure internal processing, enhance operational efficiency and gain the strategic fit to materialize the sensed and seized service opportunities. Based on the above discussion, we argue that SSAC influences competitive advantages indirectly by directly impacting three DCs (i.e., market sensing, seizing and reconfiguring). Thus, we put forward the following hypotheses:

H1: SSAC has a significant positive impact on market sensing.
H2: SSAC has a significant positive impact on market seizing.
H3: SSAC has a significant positive impact on market reconfiguring.

2.4.2 The impact of market sensing, seizing and reconfiguring on competitive advantage

DC theory represents an emerging and potentially integrative approach which emphasizes on the internal resources (e.g., SSAC) and organization of the firm, rather than on external factors to enhance the competitive advantage of the firm (Wu, 2010). The foundations of DC, such as sensing, seizing and reconfiguring play an integral role to the firm's flexible operational model, to enhance the competitiveness of the firm in rapidly changing environments (Ambrosini et al., 2009; Eisenhardt & Martin, 2000; Zollo & Winter, 2002). A strong market sensing, seizing and reconfiguring capabilities provide the firm with a first-mover advantage through increased customization, lower delivery performance, and reduced reaction time. Market sensing, as part of firm’s DCs, plays an essential role in developing firm’s competitive advantage through insights from service systems, by assessing customers' actual preferences and capturing ideas internally from a wide range of employees (Teece, 2018). Market seizing capability enhances the firm’s competitive advantage by mobilizing the resources to address needs and opportunities, and to capture value from doing so. Market reconfiguring capability, allows firms to improving the flexibility of operations, reducing costs, develop new partnerships, and consequently strengthening their customer retention. Thus, market-reconfiguring capability provides a timely response to changing customer requirements and eventually enhances the firm’s competitive advantage. Thus, we hypothesize that:

H4: Market sensing has a significant positive impact on competitive advantage.

H5: Market seizing has a significant positive impact on competitive advantage.

H6: Market reconfiguring has a significant positive impact on competitive advantage.

2.4.3 Mediating Effects

A service system’s analytics capability underpins and facilitates dynamic capabilities to respond to changes in an uncertain environment and eventually achieve competitive advantage (Barton & Court, 2012; Erevelles, Fukawa, & Swayne, 2016; Opresnik & Taisch, 2015). Since SSAC helps in planning and allocating resources to identify and enter any market, they eventually help build DCs to sense, seize and transform new service opportunities (Fischer et al., 2010). A strong dynamic capability provides the firm with a first-mover advantage through increased customization, lower delivery performance, reduced reaction time and robust strategies (Wamba, Dubey, Gunasekaran, & Akter, 2019). Therefore, it is evident that SSAC provides the firm with key resources (i.e., technology, management and personnel) that enhance DCs to achieve a competitive advantage in the market. Based on the above discussion, we posit that:

H7a: Market sensing has a significant mediating relationship between service systems analytics capabilities and competitive advantage.

H7b: Market seizing has a significant mediating relationship between service systems analytics capabilities and competitive advantage.

H7c: Market reconfiguring has a significant mediating relationship between service systems analytics capabilities and competitive advantage.

3.0 Research Method

3.1 Scale Development

Using an online survey, the study collected 251 valid responses from service systems analytics managers with a response rate of 41%. We adapted the items from past studies to fit the service systems analytics context (Appendix 1). The study identifies SSAC as a third-order, hierarchical construct with three second-order constructs management capability, technology, and personnel capability) and eleven first-order constructs (see Table 3). The study used a seven-point Likert scale with anchors ranging from strongly disagree (1) to strongly agree (7) to measure all items in the survey.

3.2 Pre-test, Pilot Test and Data Collection

Survey data were collected from the U.S. under a service analytics project in 2018 through a leading market research firm. We define the population as service systems analytics professionals in the mid-level management, who have an experience of dealing with big data analytics in service systems for at least three years. Before undertaking the main study, we conducted a pre-test over 20 random samples to confirm that the wording, format, layout and scales (5-point vs. 7-point) were appropriate. The feedback from this phase helped us to develop the final instrument. The sample represents various service systems ranging from banking, tourism to transportation, healthcare and retail.

3.3 Common Method Variance (CMV)

Since non-response bias becomes a critical issue in online survey research, we addressed this concern initially by comparing the survey participants with the overall panel regarding industry type, organization size and global operations. Also, we conducted a test using paired t-test technique to detect any anomaly between first and last 30% responses, no non-response bias was detected (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Stanko, Molina-Castillo, & Munuera-Aleman, 2012).

The study also investigated common method variance (CMV) with the help of robust procedural and statistical techniques. As part of procedural techniques, we ensured rigor in questionnaire design by removing double-barrelled or ambiguous items, clarifying the objectives of the study with adequate flexibility in answer options, using proper attention checkers (e.g., one reverse-coded item) and finally, assuring anonymity and confidentiality of responses (Esfandiar, Dowling, Pearce, & Goh, 2020). Also, we established a psychological separation between antecedents and criterion variables so that causality can be identified. As part of statistical techniques, first, we conducted Herman's single-factor test (Podsakoff & Organ, 1986), which did not show any particular factor exceeding 30% of the variance. Due to its limitations to identify small CMV (Malhotra, Kim, & Patil, 2006), we conducted the marker variable procedure (Lindell & Whitney, 2001); however, the findings show an insignificant relationship ($r=0.032$, $p>0.05$) between the marker variable and the constructs.

3.4 Data Analysis

We specified the research model as a reflective-formative as the first-order constructs are reflective (Mode A) and the second-order constructs are formative (Mode B) (Chin, 2010a; Ringle, Sarstedt, & Straub, 2012). Drawing on the findings by Becker, Klein, and Wetzels (2012), the study uses repeated indicator approach to estimate the hierarchical model with path weighting scheme. The study adopted the repeated indicator approach proposed by Wetzels, Odekerken-Schroder, and Van Oppen (2009) and Becker et al. (2012), which calculates all the constructs simultaneously instead of a separate estimate of lower-order and higher-order dimensions. In addition, this approach uses the measurement items repeatedly for the first-order, second-order and the highest-order model. The study adopted PLS-SEM for estimating the hierarchical model to reduce the complexity of the large model and establish parsimony. Due to soft modelling assumptions, it also avoids limitations regarding distributional assumptions, model identification and factor indeterminacy (Esfandiar, Sharifi-Tehrani, Pratt, & Altinay, 2019; Hair, Ringle, & Sarstedt, 2011). The study also used SmartPLS 3.0 (C. M. Ringle, Wende, & Becker, 2014) to estimate the measurement and structural model following the guidelines of hierarchical modelling (J. Becker, Beverungen, & Knackstedt, 2010; Chin, 2010).

3.5 Measurement model

Due to the hierarchical nature of the research model, we first checked convergent and discriminant validity of the first-order measurement model. Table 2 shows that the loadings (>0.70, p<0.05), composite reliability (CR >0.80) and average variance extracted (AVE >0.50) of the first-order constructs are significant (Chin, 1998a; Fornell & Larcker, 1981). Loadings indicate to what extent items reflect respective constructs, AVE measures the amount of variance of a construct against measurement error and finally, CR shows internal consistency of the items (Chin, 1998a; Fornell & Larcker, 1981; Hair Jr, Hult, Ringle, & Sarstedt, 2017).

The first-order constructs include service system planning, service system investment decision making, service system coordination, service system control, service system technology management knowledge, service system technical knowledge, service system business knowledge, service system relational knowledge, service system connectivity, service system compatibility, service system modularity, market sensing, market seizing, market reconfiguring and competitive advantages. For control variables, the collinearity test of formative variables (i.e., firm size and firm type) show evidence of minimum collinearity as the variance inflation factors (VIF) do not exceed 5 (Hair Jr et al., 2017). We also confirm discriminant validity in Table 3, which shows the square root of the AVEs in the diagonals, which exceed the intercorrelations of the construct and confirm discriminant validity (Chin, 1998b, 2010; Fornell & Larcker, 1981). Overall, the results show adequate reliability (loadings > 0.80, AVE > 0.50, CR > 0.80) and discriminant validity ($\sqrt{AVE}$ > correlations) of all the constructs and their corresponding items through their measurement model properties.

Table 2: Measurement Model: Assessment of First-Order, Reflective Model

Reflective Constructs	Items	Loadings	CR	AVE
Service system planning (SAPLN)	SAPLN1	0.918	0.942	0.850
	SAPLN2	0.934		
	SAPLN3	0.933		
	SAPLN4	0.902		
Service system investment decision making (SAIDM)	SAIDM1	0.901	0.952	0.822
	SAIDM2	0.887		
	SAIDM3	0.919		
	SAIDM4	0.919		
Service system coordination (SACOR)	SACOR1	0.892	0.945	0.811
	SACOR2	0.910		
	SACOR3	0.905		
	SACOR4	0.896		
Service system control (SACOT)	SACOT1	0.842	0.953	0.835
	SACOT2	0.856		
	SACOT3	0.879		
	SACOT4	0.870		
Service system connectivity (SACON)	SACON1	0.921	0.952	0.821
	SACON2	0.901		
	SACON3	0.906		
	SACON4	0.852		
Service system compatibility (SACOM)	SACOM1	0.904	0.942	0.831
	SACOM2	0.933		
	SACOM3	0.924		
	SACOM4	0.885		
Service system modularity (SAMOD)	SAMOD1	0.899	0.954	0.812
	SAMOD2	0.888		
	SAMOD3	0.928		
	SAMOD4	0.888		
Service system technology management knowledge (SAMGK)	SAMGK1	0.886	0.964	0.858
	SAMGK2	0.918		
	SAMGK3	0.907		
	SAMGK4	0.884		
Service system technical knowledge (SATKN)	SATKN1	0.884	0.951	0.810
	SATKN2	0.910		
	SATKN3	0.907		
	SATKN4	0.899		
Service system business knowledge (SABKN)	SABKN1	0.892	0.984	0.829
	SABKN2	0.921		
	SABKN3	0.926		
	SABKN4	0.905		
Service system relational knowledge (SAREL)	SAREL1	0.924	0.931	0.821
	SAREL2	0.921		
	SAREL3	0.928		
Market sensing (MASEN)	MASEN1	0.924	0.946	0.854
	MASEN2	0.921		
	MASEN3	0.928		

Market seizing (MASEI)	MASEI1	0.870	0.936	0.786
	MASEI2	0.900		
	MASEI3	0.898		
	MASEI4	0.879		
Market reconfiguring (MAREC)	MAREC1	0.903	0.947	0.817
	MAREC2	0.898		
	MAREC3	0.920		
	MAREC4	0.894		
Competitive Advantages (COMAD)	COMAD1	0.941	0.956	0.879
	COMAD2	0.933		
	COMAD3	0.938		
Formative construct	Items	Weights	t-value	VIF
Control variables (COVAR)	Firm size	0.964	1.869	1.059
	Firm type	0.577	1.209	1.059

Table 3: Correlations and AVEs*

	SAPLN	SAIDM	SACOR	SACOT	SACON	SACOM	SAMOD	SAMGK	SATKN	SABKN	SAREL	MASEN	MASEI	MAREC	COMAD
Planning (SAPLN)	**0.922**														
Inv. Dec. Making (SAIDM)	0.540	**0.906**													
Coordination (SACOR)	0.530	0.551	**0.901**												
Control (SACOT)	0.447	0.459	0.560	**0.914**											
Connectivity (SACON)	0.598	0.512	0.497	0.584	**0.906**										
Compatibility (SACOM)	0.535	0.401	0.481	0.566	0.453	**0.912**									
Modularity (SAMOD)	0.490	0.515	0.507	0.468	0.374	0.417	**0.901**								
Tech. mgm. Knowledge (SAMGK)	0.488	0.393	0.447	0.537	0.519	0.493	0.401	**0.926**							
Technical Knowledge (SATKN)	0.421	0.552	0.681	0.467	0.533	0.524	0.470	0.530	**0.901**						
Business Knowledge (SABKN)	0.525	0.560	0.538	0.585	0.585	0.482	0.482	0.465	0.487	**0.911**					
Relational Knowledge (SAREL)	0.445	0.487	0.454	0.409	0.401	0.547	0.513	0.557	0.480	0.530	**0.906**				
Market Sensing (MASEN)	0.498	0.433	0.494	0.546	0.533	0.493	0.477	0.472	0.506	0.445	0.521	**0.924**			
Market Seizing (MASEI)	0.495	0.516	0.421	0.558	0.502	0.539	0.552	0.415	0.477	0.454	0.490	0.536	**0.887**		
Reconfiguring (MAREC)	0.426	0.502	0.588	0.435	0.591	0.422	0.511	0.478	0.488	0.501	0.456	0.514	0.542	**0.904**	
Competitive Advantages (COMAD)	0.424	0.459	0.453	0.521	0.476	0.561	0.532	0.555	0.488	0.578	0.406	0.593	0.522	0.551	**0.899**

*Square root of AVE on the diagonals.

3.6 Structural Model

The study estimated path coefficients, t-statistics and R^2 in the structural model (Falk & Miller, 1992) in Table 4 and Figure 3 in the following after successful confirmation of reliability and validity of the measurement model. The findings show a standardized path coefficient of 0.831 from SSAC to sensing, 0.866 from SSAC to seizing, and 0.831 from SSAC to reconfiguring. All these path coefficients are significant, thus supporting H1-H3 at $p<0.01$. The findings also provide a standardized path coefficient of 0.395 from sensing to competitive advantage, 0.244 from seizing to competitive advantage, and 0.291 from reconfiguring to competitive advantage, thereby supporting H4, H5 & H6 at $p<0.01$.

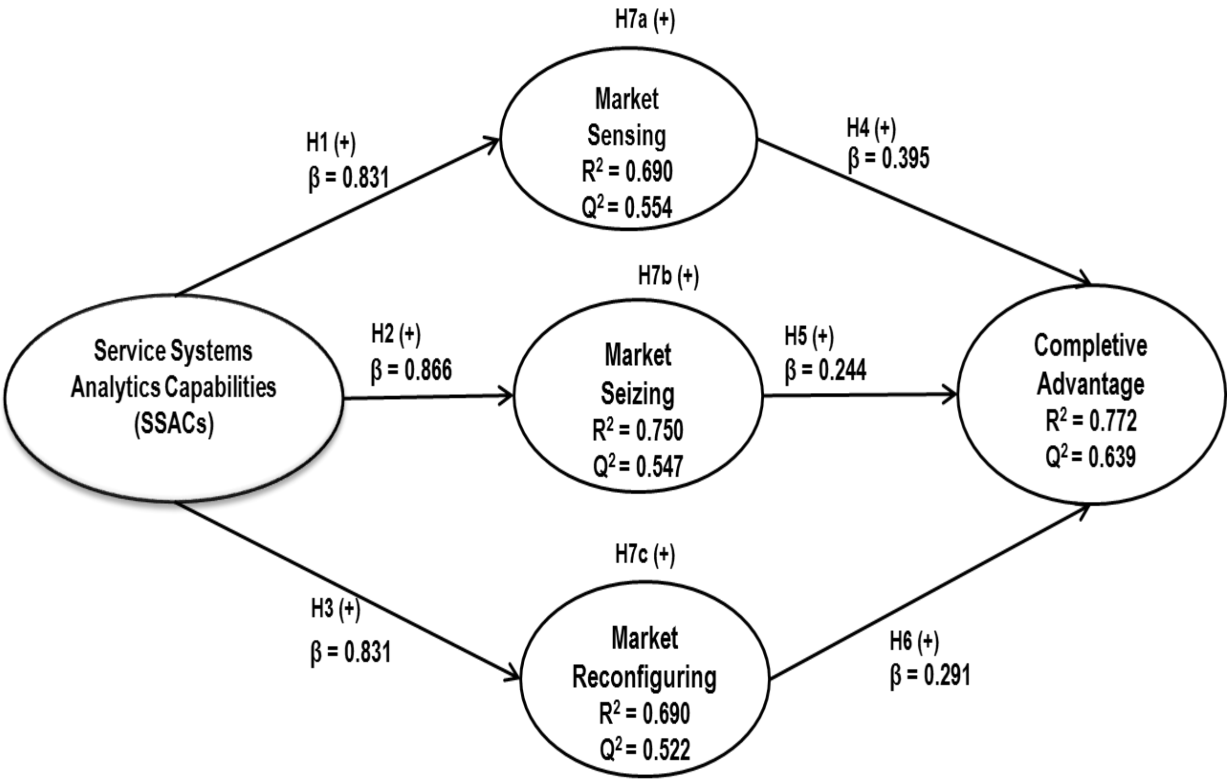

Figure 3: Structural model.

Table 4: Results of the Structural Model

Hypotheses	Main Model			Path coefficients	Standard error	*t*-statistic
H1	SSAC	→	SENSE	0.831	0.032	25.793
H2	SSAC	→	SEIZE	0.866	0.024	35.767
H3	SSAC	→	RECON	0.831	0.033	24.984
H4	SENSE	→	COMAD	0.395	0.091	4.346
H5	SEIZE	→	COMAD	0.244	0.084	2.907
H6	RECON	→	COMAD	0.291	0.088	3.295

As part of estimating process of the mediating effect between SSAC-SENSE-COMAD, SSAC-SEIZE-COMAD and SSAC-RECON-COMAD, the study followed the procedures by Preacher and Hayes (2008), Hayes, Preacher, Myers, Bucy, and Holbert (2011) and bootstrapped the sampling distribution of indirect effects using 95% of the confidence interval. The mediating path-1 from SSAC via SENSE to COMAD is the product of the path coefficients from SSAC to SENSE and from SENSE to COMAD, which is 0.328, significant at $p<0.01$. Similarly, we estimate the mediating path-2 from SSAC via SEIZE to COMAD, which is 0.211, significant at $p<0.01$ and path-3 from SSAC via RECON to COMAD, which is 0.242, significant at $p<0.01$. Since all the indirect effects are significant and positive, the findings provide strong support for SENSE, SEIZE and RECON as full mediators between SSAC and COMAD (Hair Jr et al., 2017). The findings also show that two control variables (i.e., firm size and type) do not have any significant impact on COMAD.

Using the coefficient of determination (R^2), the study also estimates the overall variance explained by the model, which is 0.690 for SENSE, 0.750 for SEIZE, 0.690 for RECON and 0.772 for COMAD. We identify these coefficients as large effect sizes according to the R^2 guidelines set out by Cohen (1988). These findings provide solid evidence of SSAC on sensing, seizing reconfiguring and competitive advantages. As part of the testing predictive validity of the nomological model, the study further estimates the Stone-Geisser's Q^2 value, which varies between 0.522 and 0.639 and then confirms adequate predictive validity (Chin, 2010).

4.0 Findings and discussion

Drawing on the dynamic capability theory, this study identifies that SSAC influences competitive advantage through market sensing, seizing and reconfiguring. The findings based on 251 service analytics professionals in the U.S. confirming management, technology and personnel capabilities as the key dimensions. Although all the dimensions are significant, the magnitude of the difference is very minimum, such as personnel capability, followed by management capability and technology capability. Overall, the findings confirm a significant association between third-order, second-order and first-order constructs. For example, the management capability reflects service analytics planning, decision making, coordination and control. While analysing the structural model, we identify that SSAC has a significant positive impact on market sensing (β=0.831, R^2=0.690), seizing (β=0.866, R^2=0.750) and reconfiguring (β=0.831, R^2=0.690), which emerge as full mediators between SSAC and competitive advantages. Overall, the model explains 77% of the variance of competitive advantages.

4.1 Implications for theory

The findings of this study make some important theoretical contributions. Drawing on the theory of DC (Teece 2014, 2016), we have conceptualized SSAC as a higher-order construct which comprises of three interrelated second-order constructs such as personnel capability, management capability and technology capability. Therefore, while identifying the important dimensions of SSAC, our findings offer some insights on dimensions and subdimensions, which need to be underscored when combining and organizing various capabilities of the firm that are needed to build SSAC. This result supplements the emerging and existing literature on big data analytics capability of the firms (Akter et al., 2016; Fosso Wamba et al., 2017). For example, our results highlight the fundamental role of the service firm's personnel capability, management capability and technology capability, which constitute the SSAC, in enhancing DCs directly.

In addition, we present a nomological network that integrates different literature of the analytics environment. Our findings extend prior research on the relationship between service analytics capabilities, dynamic capabilities and firm's competitive advantage (Mikalef, Boura, Lekakos, & Krogstie, 2019; Mikalef, Pappas, Krogstie, & Giannakos, 2018; Zollo et al., 2016). We show that SSAC plays a key role in influencing the firm's competitive advantage by strengthening the firm's service sensing, seizing and reconfiguring capabilities. This finding bears immense significance for service systems across the world to sense, seize and reconfigure various access and affordability challenges. The study further provides empirical support for the relationship between SSAC and improved competitive advantage, while identifying the crucial mediating role of the dynamic capabilities that need to be developed in the big data environment.

4.2 Implication for practice

From the practical standpoint, the findings of the study emphasize the following implications for any service system including healthcare, telecommunications, transportation, retail, banking etc. First, the findings build awareness of the SSAC and provide the initial guideline to the practitioners and managers who are exploring the potential benefits of SSAC to address competitive goals. Second, this study provides some insights into crucial SSAC dimensions on which managers should focus on during their big data adoption-and-use projects for developing analytics capabilities. The dimensions are (i) management capability which is made of planning, decision making, coordination and control; (ii) technology capability comprises of SSAC connectivity, compatibility and modularity; and (iii) personnel capability, which refers to the people, is probably the most important dimension on which managers should concentrate on. Finally, the study underscores the efficacy of dynamic capabilities in terms of market sensing, seizing and reconfiguring opportunities in reshaping competitive advantage. Since almost all service systems are keen to reshape competitive advantages, this study provides an integrated SSAC framework to build dynamic capabilities to achieve competitive advantages.

4.3 Limitations and future research directions

There are a few issues which have constrained the outcome of the present study. First, in this study, we adopt a cross-sectional approach which only allows the collection of data about the phenomena under study at one point in time. To overcome this issue, future research can adopt a longitudinal approach which would track the changes in the proposed nomological network over time. Moreover, a mixed-methods approach, combining both qualitative and quantitative research methods, can be useful to achieve deep insights of SSAC and its impact on various global challenges (e.g., poverty, healthcare, food security etc.). Second, the study offers insights into a single country-based perspective focusing on the U.S. Future studies can collect data from various countries. Moreover, the integration of cultural dimensions into the proposed model could bring an interesting outcome. This study lacks the assessment of unobserved heterogeneity, the realization of which could have strengthened both the structural model and the measurement model in an SEM analysis (Becker, Rai, Ringle, & Völckner, 2013). Overall, big data and AI projects have become intertwined in service systems due to the application of machine learning and deep learning with statistical approaches on fast moving data (Davenport & Bean 2018). Thus, AI is an extension of BDA in service systems, which need to be investigated to establish the foundation of advanced analytics capabilities.

4.4 Conclusions

Reflecting on the challenges of global service systems and the exploding growth of big data, this research presents an SSAC model. There has been a cursory work on service analytics and there is a significant gap in the literature to explore SSAC and its direct and indirect impact on competitive advantages. Synthesising literature on service systems, big data and dynamic capabilities, we test and validate an SSAC model and elaborate on the role of each dimension and subdimension. Thus, this paper presents a useful starting point to understand the significance of SSAC in global data economy and their effects on outcome constructs through dynamic capabilities.

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Appendix 1: Survey Measures

2nd-order constructs	Type	1st-order constructs	Type	Item labels	Items	Sources
Service system analytics management capability	Molecular	Service planning	Reflective	SAPLN1	We continuously examine the innovative opportunities for the strategic use of big data analytics in service systems.	(Kim, Shin, & Kwon, 2012)
			Reflective	SAPLN2	We enforce adequate plans for the introduction and utilization of big data analytics in service systems.	
			Reflective	SAPLN3	We perform big data analytics planning processes in systematic and formalized ways in service systems.	
			Reflective	SAPLN4	We frequently adjust big data analytics plans to better adapt to changing conditions in service systems.	
		Service investment decision making	Reflective	SAIDM1	When we make big data analytics investment decisions in service systems, we think about and estimate the effect they will have on the productivity of the employees' work.	
			Reflective	SAIDM2	When we make big data analytics investment decisions, we consider and project about how much these options will help end-users make quicker decisions in service systems.	
			Reflective	SAIDM3	When we make big data analytics investment decisions in service systems, we think about and estimate the cost of training that end-users will need.	
			Reflective	SAIDM4	When we make big data analytics investment decisions in service systems, we consider and estimate the time managers will need to spend overseeing the change.	
		Service coordination	Reflective	SACOR1	In our organization, big data analysts and line people in service systems meet frequently to discuss important issues both formally and informally.	
			Reflective	SACOR2	In our organization, big data analysts and line people from various service systems frequently attend cross-functional meetings.	
			Reflective	SACOR3	In our organization, big data analysts and line people in service systems coordinate their efforts harmoniously.	
			Reflective	SACOR4	In our organization, information is widely shared between big data analysts and line people so that those who make decisions or perform jobs have access to all available know-how in service systems.	

		Service control	Reflective	SACON1	In our organization, the responsibility for big data analytics development in service systems is clear.	
			Reflective	SACON2	We are confident that big data analytics project proposals are properly appraised in service systems.	
			Reflective	SACON3	We constantly monitor the performance of the big data analytics function in service systems.	
			Reflective	SACON4	Our big data analytics department is clear about its performance criteria in service systems.	
Technology capability	Molecular	Service connectivity	Reflective	SACON1	Compared to rivals within our industry, our organization has the foremost available analytics driven service systems.	(Kim et al., 2012)
			Reflective	SACON2	All remote, branch, and mobile offices are connected to the central office for analytics-driven service systems.	
			Reflective	SACON3	Our organization utilizes open service systems network mechanisms to boost big data analytics connectivity.	
			Reflective	SACON4	There are no identifiable communications bottlenecks within our organization when sharing big data analytics insights in service systems.	
		Service compatibility	Reflective	SACOM1	Software applications can be easily transported and used across multiple big data analytics platforms in service systems.	
			Reflective	SACOM2	Our user interfaces provide transparent access to all platforms and applications in service systems.	
			Reflective	SACOM3	Big data analytics-driven information is shared seamlessly across our organization, regardless of the location of service systems.	
			Reflective	SACOM4	Our organization provides multiple big data analytics interfaces or entry points for external end-users of service systems.	
		Service modularity	Reflective	SAMOD1	Reusable software modules are widely used in new big data analytics model development for service systems.	
			Reflective	SAMOD2	End-users utilize object-oriented tools to create their own big data analytics applications in service systems.	
			Reflective	SAMOD3	Object-oriented technologies are utilized to minimize the development time for new big data analytics applications in service systems.	
			Reflective	SAMOD4	Applications can be adapted to meet a variety of needs during big data analytics tasks in service systems.	
	M		Reflective	SATKN1	Our big data analytics personnel are very capable in terms of programming skills in service systems.	(Kim et al., 2012)

Personnel capability		Service technical Knowledge	Reflective	SATKN2	Our big data analytics personnel are very capable in terms of managing project life cycles in service systems.	
			Reflective	SATKN3	Our big data analytics personnel are very capable in the areas of data and network management and maintenance in service systems.	
			Reflective	SATKN4	Our big data analytics personnel create very capable decision support systems.	
		Service technology management knowledge	Reflective	SAMGK1	Our big data analytics personnel show superior understanding of technological trends in service systems.	(Kim et al., 2012; Terry Anthony Byrd, 2000; Tippins & Sohi, 2003)
			Reflective	SAMGK2	Our big data analytics personnel show superior ability to learn new technologies in service systems.	
			Reflective	SAMGK3	Our big data analytics personnel are very knowledgeable about the critical factors for the success of service systems in our organization.	
			Reflective	SAMGK4	Our big data analytics personnel are very knowledgeable about the role of big data analytics as a means, not an end in service systems.	
		Service business knowledge	Reflective	SABKN1	Our big data analytics personnel understand our organization's policies and plans for service systems at a very high level.	(Kim et al., 2012)
			Reflective	SABKN2	Our big data analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions for service systems.	
			Reflective	SABKN3	Our big data analytics personnel in service systems are very knowledgeable about business functions.	
			Reflective	SABKN4	Our big data analytics personnel in service systems are very knowledgeable about the business environment.	
		Service relational knowledge	Reflective	SAREL1	Our big data analytics personnel in service systems are very capable in terms of planning, organizing, and leading projects.	(Kim et al., 2012)
			Reflective	SAREL2	Our big data analytics personnel in service systems are very capable in terms of planning and executing work in a collective environment.	
			Reflective	SAREL3	Our big data analytics personnel in service systems are very capable in terms of teaching others.	
			Reflective	SAREL4	Our big data analytics personnel in service systems work closely with customers and maintain productive user/client relationships.	
Dynamic capabillity	Molecul	Market Sensing	Reflective	MASEN1	We use analytics in service systems for tracking competitors' strategies and tactics	Fang et al. (2014)
			Reflective	MASEN2	We use analytics in service systems for learning about the macro-market environment	

			Reflective	MASEN3	We use analytics in service systems for identifying and understanding market trends	Wilden, & Gudergan, (2015).
		Market Seizing	Reflective	MASEI1	We invest in service systems in finding solutions for our customers.	
			Reflective	MASEI2	We adopt the best practices in service systems in our sector.	
			Reflective	MASEI3	We respond to defects in service systems pointed out by employees.	
			Reflective	MASEI4	We change our practices in service systems when customer feedback gives us a reason to change.	
		Market reconfiguring	Reflective	MAREC1	We constantly implement new kinds of management methods in service systems.	
			Reflective	MAREC2	We frequently improve our customer relationship strategy in service systems.	
			Reflective	MAREC3	We substantially renew business processes in service systems.	
			Reflective	MAREC4	We constantly renew the ways of achieving our targets and objectives for service systems.	
Competitive Advantages	NA	NA	Reflective	Using big data analytics in service systems ____:		(Schilke, 2014)
				COMAD1	We have gained strategic advantages over our competitors.	
				COMAD2	We have a large market share.	
				COMAD3	Overall, we are more successful than our major competitors.	