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How Talent Capability Can Shape Service Analytics Capability in the Big Data Environment?

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Abstract

We know very little about how big data driven service analytics capabilities (SAC) are built in data driven service organizations and the potential role of talent capability in facilitating overall SAC and the impact of both on firm performance (FPER). Drawing on the dynamic capabilities (DC) approach, this study investigates the link between SAC and FPER examining the mediating role of talent capability and the moderating influence of a firm's strategic alignment. On the basis of two Delphi studies and survey data from 267 service analysts in the U.S. and France, the findings show that even though SAC are built on technology, talent and information capabilities, their overall impact on firm performance is mediated by the level of talent capability of service analytics managers. The findings also confirm the critical moderating impact of strategic alignment between dynamic talent capability and firm performance in the big data environment.

Keywords: Big data analytics, firm performance, information capability, strategy alignment, talent capability, technology capability.

1 Introduction

We live in an era of big data. Because of big data, service analysts now know more about their customers and provide solid insights for improved decision making and better performance (Kiron, Prentice, and Ferguson 2014). Marketing managers in service organizations that inject big data analytics (BDA) into their decision making experience 5–6% higher productivity in their firm performance (McAfee and Brynjolfsson 2012a). Since big data is identified as ‘the next frontier for innovation, competition, and productivity’ (Manyika et al. 2011, , p.1), capitalizing on big data depends on leveraging its analytics capabilities. Thus the challenge for service organizations in the data economy is to identify analytics capabilities that influence their productivity.

Although big data analytics has become more mainstream for service firms, leveraging analytics capabilities continues to be a challenge. Specifically, little is known about effective operationalization of big data driven service analytics capability (SAC) with a special focus on talent capability. Illuminating the role of talent capability, Ransbotham, Kiron, and Prentice (2015, p.5) state, “talent is clearly a key driver in innovating and gaining a competitive advantage with analytics”. Despite the importance of talent capability in service analytics environment, many companies still struggle with how to use it in a big data environment.

Motivated by this challenge, the main research questions we address are: (i) what are the dimensions of service analytics capabilities (ii) to what extent the contribution of service analytics capabilities to firm performance is mediated by talent capability. We also investigate the extent to which the impact of service analytics capabilities on firm performance is conditioned by the firm’s strategic alignment (Lopez-Cabrales, Pérez-Luño, and Cabrera 2009). To answer these research questions, we conceptualize service analytics capabilities (SACs) as dynamic capabilities, which are organizational routines, clearly measurable and

distinct from a firm's strategy and performance (Eisenhardt and Martin 2000). Making this distinction allows us to investigate claims regarding the effect of SACs on firm performance and explore the impact of strategic alignment.

Explaining the coherence between service analytics capability and strategic alignment enhances firm performance, which extends dynamic capability (DC) theory and the emerging service analytics literature. Specifically, this paper makes three main contributions. First, this study extends DC theory in strategic services marketing by clearly explaining how higher-order dynamic analytics capabilities and strategic alignment work together to improve performance service organizations in a big data context. This packaging of dynamic service analytics capabilities and strategic alignment extends the DC and service analytics literatures in academia and practice by showing how they are intertwined in establishing and sustaining performance (Teece 2014). Second, our findings improve service analytics research by identifying technology, talent and information capabilities as higher-order, dynamic service analytics capabilities, which enhance firm performance. These findings contribute to answering "what capabilities (technical and non-technical) should an organization acquire to succeed in data driven services marketing efforts?" arguably one of the most interesting questions in the field of big data driven service research today (Phillips-Wren et al. 2015, p. 465). Third, the study makes an empirical contribution by identifying the critical role of talent capability of service analysts as a mediator and firm's strategic alignment as a moderator in the dynamic talent capability-firm performance relationship.

2 LITERATURE REVIEW AND THEORIES

The dynamic capabilities (DCs) view is based on the extension of the resource-based view (RBV) of the firm. While DCs illuminate the sensing, seizing and reconfiguration capabilities of existing resources, RBVs are primarily confined to shaping the ordinary capabilities of existing resources. As such, DCs refer to the higher level orchestration of ordinary capabilities to cope with the rapidly changing business environment with a view to firm level value creation, competitive advantage and growth. This section critically discusses how DCs are different from RBVs, their relation to firm performance, and identifies service analytics capabilities as DCs.

2.1 From RBV to Dynamic Capability and Firm Performance

The RBV (Barney 1991), which refers to bundles of heterogeneous resources which are valuable, rare, inimitable and non-substitutable, has been employed as a leading theoretical framework in marketing capability literatures to explain why some firms are more successful and how they create and sustain a long-lasting competitive advantage. Considering extensive applications of the RBV in the broader marketing literatures, Kozlenkova, Samaha, and Palmatier (2014) contend that strategic marketing research is built on the RBV to a large extent. Despite a wide range of applications of the RBV since its inception in the early nineties, researchers have been constantly examining, reviewing and criticizing its utility in the literatures of strategic management (Nason and Wiklund 2015) and strategic marketing (Evanschitzky 2007). A key criticism of the RBV is that it has been unable to explain how and why some firms sustain competitive advantage over others in rapidly changing market environments. This has led scholars to extend the RBV to dynamic capability (Eisenhardt and Martin 2000). For example, Griffith, Noble, and Chen (2006) postulate that the way a firm like Kodak responded to technological change in the digital photography industry indicated presence of an important component of DC.

To sustain competitive advantage, a capability view supplements the RBV by identifying which capabilities help firms to employ their resources especially in dynamic environments (Vanpoucke, Vereecke, and Wetzels 2014). Researchers have observed that firms are unable to maintain competitive advantages in dynamic environments unless they reconfigure their resources to accommodate changing needs (Grant 1996; Ambrosini, Bowman, and Collier 2009). It is argued that DCs enable firms to integrate, reconfigure, gain and release resources in order to cope effectively with changing circumstances and achieve new resource configurations as their markets advance (Vanpoucke, Vereecke, and Wetzels 2014). Accordingly, Helfat et al. (2009) assert that DCs allow firms to create, extend and modify their tactics to ensure their survival in fast changing environments.

2.2 How are DCs different from other resources?

As noted above, DCs are the capacity of an organization to purposefully create, extend or modify its resource base (Helfat et al. 2009, 30) to achieve competitive advantage. In continued volatile service markets where competitive scenarios are constantly shifting into a new paradigm, DCs enable firms to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Teece, Pisano, and Shuen 1997, 516). DCs are different from other resources as they enable a firm toward high-payoff activities which warrant orchestrating the firm's resources to accommodate rapidly shifting business environments. This indicates that whereas the ordinary capabilities of a firm are concerned about doing things right, DCs are more about doing the right things at the right moment by constantly innovating unique products and services that markets expect from time to time (Teece 2014).

2.3 Impact of DCs on firm performance

Scholars suggest that there are several ways through which DCs can have a positive impact on firm performance. First, DCs can enhance financial growth by innovating new processes and developing and offering unique services compared to competitors who rely solely on ordinary capabilities (Ghobadian et al. 2007). Second, DCs can accelerate the speed of firms' responses to environmental changes making them quicker than those of other firms and thus enhancing the efficiency and effectiveness of their service operations. Finally, DCs allow firms previously unavailable sets of decision options consequently offering a greater scope of increased performance (Eisenhardt and Martin 2000). For example, Amazon used analytics to optimize service performance by linking this to the talent capability of service analysts (Sparrow, Hird, and Cooper 2015).

2.4 Defining service analytics capabilities as dynamic capabilities

DCs are referred to as higher level capabilities that orchestrate a firm's resources to enhance firm performance in changing environments (Teece 2014). DCs enable firms to establish competitive advantages in innovation driven competition. The foundation of the DC framework is suitable for the current big data environment in which analytics professionals are keen to capitalize on DCs to gain an edge in the market. We define SAC as a DC because it can generate superior profits by solid insights in a constantly changing multi-channel business environment. SAC is also considered to be a DC because the holistic analytics process must be able to adapt to environmental change to facilitate continuous generation of solid insights for better decision making. Thus, firms in a dynamic big data environment focus on developing strong analytics capabilities that can adapt, orchestrate and innovate with market and technology developments (Teece 2014).

3 RESEARCH MODEL AND HYPOTHESES

To develop a service analytics capability (SAC) model, first, we conducted a systematic review to identify the dimensions of SAC in the big data environment. This revealed three major dimensions: technology, talent and information capabilities (Kiron, Prentice, and Ferguson 2014; Davenport, Barth, and Bean 2012; Davenport and Harris 2017). Second, we conducted two Delphi studies to investigate the components of these three primary analytics capabilities. Overall, we found support for 12 components (i.e., *technology capability*: connectivity, compatibility, modularity and privacy; *talent capability*: technical knowledge, technology management knowledge, business knowledge and relational knowledge; *information capability*: completeness, accuracy, format and currency) under the three primary capabilities proposed in the research model (see Fig. 1). Drawing on dynamic capabilities (DCs) approach, the research model conceptualizes the three primary capabilities as second-order DCs (routines that reconfigure first-order DCs) and 12 components as first-order DCs (routines that reconfigure the organizational resource base) (Schilke 2014). The review and the Delphi findings show that an adaptation of the resource base can help these DCs match external forces to configure resources.

PLACE FIGURE 1 HERE

3.1 Technology capability, talent capability, and firm performance

Technology capability refers to the ability of the analytics infrastructure (e.g., networks and applications), to have both a direct impact on firm performance and an indirect impact through talent capability. Technology capability includes connectivity, compatibility, modularity and adaptability. *Connectivity* refers to linking and analysing big data from various units. For example, United Parcel Service (UPS) examines usage patterns and complaints to predict customer defection (Davenport 2006). *Compatibility* focuses on real time decision making using cloud technologies and rapid analysis (Davenport and Harris

2017). For example, Amazon applies collaborative filtering using various customer data to predict “you might also want...” prompts (Manyika et al. 2011). *Modularity* refers to the flexibility of an analytics platform to develop dynamic models focusing on changing opportunities. For example, Wal-Mart developed Retail Link so that suppliers would know when stores should be restocked rather than waiting for an order from Wal-Mart stores (Manyika et al. 2011). Finally, *privacy* refers to the ability of a BDA platform to offer a safe and protected environment for user information. For example, names and addresses, social security numbers, credit card numbers, and financial information could be another challenge for big data management. Accordingly, we posit that:

H1: Technology capability has a significant positive impact on firm performance in the BDA environment.

Technology capability enables data scientists to develop and implement the technical aspects of a big data firm. For a sophisticated analytics capability, it is imperative to build and enhance technology capability so that data scientists can flexibly adapt in line with uncertain business conditions or corporate strategies. For example, citing the impact of technology capability on talent capability, Davenport (2013,p.67) states that “ innovative technologies of many kinds had to be created, acquired, and mastered ... To complement them, new “agile” analytical methods and machine-learning techniques are being used to produce insights at a much faster rate”. Thus, we hypothesize that:

H2: Technology capability has a significant positive impact on talent capability in the BDA environment.

3.2 Information capability, talent capability and firm performance

Information capability refers to the ability to provide complete, accurate, well formatted, and current information that is tailored to changing business needs and directions. For example, Netflix analyzes customer feedback from over one billion reviews to provide robust information to customers in terms of movie preferences (Akter and Wamba 2016). Indeed, the

quality of decision making by data scientists within an organization depends on the ability to manage information management capability. In other words, this capability enables overall BDA, which in turn influences firm performance. While technology capability provides the foundation for BDA, the information is of critical importance in providing solid insights (Davenport, Barth, and Bean 2012). Specifically, in the data economy, it is important to know the components of solid information and how they can be exploited to enhance analytics capability. Thus, we hypothesize:

H3: Information capability has a significant positive impact on talent capability in the BDA environment.

H4: Information capability has a significant positive impact on firm performance in the BDA environment.

3.3 The mediating role of talent capability

Talent capability refers to the ability of a service analytics professional (e.g., someone with analytics skills or knowledge) to perform assigned tasks in the big data environment. To leverage BDA, firms must recruit and retain talented frontline employees so that they can play the role of a conduit between technology platform and firm performance. According to Constantiou and Kallinikos (2014), technical and technological ‘know-how’ and other types of knowledge are talent capabilities that can create or sustain competitive advantage. Although technology plays a critical role in analytics facilitating firm performance, when using technology it is important to have the right talent to provide solid insights. Thus, we posit that:

H5.1: Talent capability mediates the relationship between technology capability and firm performance.

As argued by McAfee and Brynjolfsson (2012b) and Kiron et al. (2014), service analysts should be empowered with statistical, contextual, and cognitive skills, and other related knowledge so that they can turn data into solid insights for customer service. Service analysts can make critical decisions looking at predictive models to attract and retain customers (Ransbotham, Kiron, and Prentice 2015). Thus, we put forward the hypothesis:

H5.2: Talent capability mediates the relationship between information capability and firm performance.

3.5 The moderating role of dynamic analytics capabilities and strategic alignment (DTCSA)

Strategic alignment determines how the firm should interact with its service analysts. Learning and innovation, particularly when expert talent is involved, benefit from “light-touch” management (Teece 2011, p.337) including an agile, non-traditional, and pragmatic approach to employment policies and practices (Welbourne 2011). The role of service analysts in acquiring and mobilizing dynamic analytics capabilities is part of strategic alignment. Ransbotham, Kiron, and Prentice (2015) argue that the extent and speed to which the firm’s talent capability will be aligned with strategy is contingent upon the strength of the firm’s dynamic capabilities. For instance, firms with strong dynamic capabilities can adopt a differentiated service strategy by offering more customized products and services whereas firms with lower dynamic capabilities are unable to afford to adopt such a strategy. In this paper, we argue that the impact of dynamic talent capability on firm performance is dependent upon the degree of strategic alignment. Thus, we hypothesize:

H6: Strategic alignment has a significant impact on the relationship between dynamic talent capability and firm performance.

4 Research Methodology

4.1 Scale Development

We developed all the items of the constructs using prior literature and adapted them to fit the business analytics context (Appendix 1). The content validity of the adapted items was checked and validated by eight experienced academics and practitioners in big data analytics. Next, we conducted a pilot test of the questionnaire by collecting data from 52 respondents recruited from various big data analytics groups listed on LinkedIn (Pavlou and Fygenon 2006). We used a 7-point Likert scale to measure all our constructs and controlled the contextual variables (e.g., firm size, firm type and country) to avoid any bias.

4.2 Survey

The participants in the study are part of the panel members of a leading market research firm having at least 3 years' big data analytics experiences in the services sector. Using simple random sampling, we collected 135 valid responses from the U.S. and 132 responses from France. While conducting the survey in France, we ensured reliability of the translation by a professional translator who converted the English survey into French and then back into English. Also, a bilingual member of the research team went through the two versions of the survey to validate the translation.

4.3 Data Analysis

We applied Partial Least Squares (PLS), a variance based structural equation modelling technique, to estimate multiple interdependent and hierarchical relationships. We used PLS because it ensures *factor determinacy* by directly estimating latent variable scores, *factor identification* by introducing flexible residual covariance structure, and above all *robust prediction* for a hierarchical model (Wetzels, Odekerken-Schroder, and Van Oppen 2009). Using the software package SmartPLS (Version 3) (Ringle, Wende, and Becker 2015), we

applied nonparametric bootstrapping with 1000 replications and a path weighting scheme for the inside approximation to compute significance levels (Hair et al. 2013). Specifically, we applied the repeated indicator approach to calculate the latent variable scores of the second-order, reflective (Mode A) constructs including technology, talent and information capability. The reflective modelling is based on the fact that the items are manifestations of constructs, that is, changes in the constructs cause changes in the items ($LVs \rightarrow MVs$).

5 Findings

5.1 Measurement Model

Concerning the initial examination of the measurement model, the loadings, composite reliabilities (CR), and average variance extracted (AVE) of the first-order constructs are shown in Table 1. All the item loadings (> 0.70), CRs (> 0.70) and AVEs (> 0.50) are significant according to the established guidelines in PLS modelling (Hair et al. 2013; Chin 2010). The higher average of item loadings (> 0.80 in our case) ensures that they converge well in measuring the pertinent construct. In addition, CRs and AVEs confirm scale reliability and high internal consistency as they exceed their respective cut-off values.

To confirm discriminant validity, we calculated the square root of the AVEs in the diagonals of the correlation matrix in Table 2 as suggested in the PLS literature (Chin 1998, 2010; Fornell and Larcker 1981). This test confirms that constructs are theoretically distinct from each other and do not reflect similar concepts. These findings are further substantiated by examining cross loadings which confirm that items have stronger loadings on their respective constructs than other constructs (Fornell and Bookstein 1982). Overall, the finding present a robust measurement model with strong convergent validity (item loadings > 0.80), scale reliability (AVE > 0.50 , CR > 0.80) and discriminant validity ($\sqrt{AVE} > \text{correlations}$).

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5.2 Higher-order Measurement Model

Whereas the assessment of the first-order constructs is based on loadings/weights of the manifest variables, the assessment of the higher-order constructs is based on the relationship between the first-order and second-order constructs. Since we followed a repeated indicator approach to estimate the second-order constructs, the relationship is represented by the path-coefficients between the first and second orders. For example, the second-order technology construct consists of 12 items (3+3+3+3), representing connectivity (91%), compatibility (87%), modularity (89%), and privacy (86%) respectively. Similarly, talent capability (=12 items) is reflected by analytics management knowledge (92%), technical analytics knowledge (93%), business knowledge (92%) and relational knowledge (91%). Information capability (=12 items) is reflected by completeness (86%), currency (87%), format (90%) and accuracy (88%). Table 3 shows the relative strength of associations between first and second-order constructs through the beta coefficients, which are all significant at $p < 0.01$.

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5.3 Structural Model

The study estimated the hypothesized relationships between the second-order technology-talent-information capabilities and firm performance in order to assess the validity of the structural model. Table 4 shows that all the path coefficients in the main model are significant at $p < 0.05$, which supports H1-H4. The study also analyses the mediating effect of talent capability on both the TECCAP-TALCAP-FPER link and the INFCAP-TALCAP-FPER links. The results confirm the strong mediating effects of TALCAP in both links as the z -value exceeds 1.96 ($p < 0.05$) (Sobel 1982; Iacobucci 2008). These findings support H5.1 and H5.2. Using the VAF (Variance Accounted For) value, we estimated the size of indirect effect

as a ratio to the total effect (Hair Jr et al. 2013). The findings show that about 35% of the total effect of TECCAP on FPER and about 29% of the effect of INFCAP on FPER are caused by TALCAP. Thus, TALCAP is found to be a significant partial mediator in estimating the effects of other SACs on FPER. The findings also show that the degree of variance explained by the model in terms of R^2 was 0.608 for TALCAP and 0.508 for FPER, which are significant (Cohen 1988). In addition, using the PLS product-indicator approach (Chin, Marcolin, and Newsted 2003), we estimated the moderating effect of DTCSA on FPER. The interaction constructs were created by multiplying TALCAP with DTCSA (Chin, Marcolin, and Newsted 2003). The findings provide a standardized beta of 0.153 for the TALCAP*DTCSA-FPER link, which is significant at $p < 0.05$ (Henseler and Fassott 2010). Thus the results provide support for the moderating impact of strategic alignment on the relationship between talent capability and firm performance (H6). Similarly, we investigated the impact of control variables (COVA) on FPER and the results show that the path coefficient is not significant. All these findings are discussed in the next section.

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6 Discussion

6.1 Main Findings

The aim of our study was to conceptualize how talent capability will affect firm performance in the big data environment by influencing other capabilities. We tested the hypothesized relationships using survey data from 267 service analytics professionals in the U.S. and France. The findings indicate that technology, talent and information capabilities are significant predictors of firm performance. The critical role of talent capability is illuminated by its significant mediating effects ($VAF = 35\%$) on the relationship between technology capability and firm performance as well as information capability and firm performance (VAF

= 29%) respectively. These findings indicate that the success of SAC is largely influenced by talent capability, which can be developed by recruiting people with sound analytical skills and preparing the current workforce through formal training programs (Ransbotham, Kiron, and Prentice 2015). The findings clearly show that deriving superior firm performance from SAC is dependent on building strong talent capabilities that link overall capabilities with performance. This finding is aligned with the recent development in the Bank of England, which used diverse talent with esoteric background to process vast amount of data for various models with regard to unemployment, consumer pricing, and productivity (Fitzgerald 2016). Strategic alignment was found to be a significant moderator ($\beta=0.153$, $f^2=0.177$) of the relationship between talent capability and firm performance. This finding shows that framing a clear analytics vision and culture are important both at the talent level and the company-wide level to deploy scarce resources to meet market needs and gain a superior performance. According to Teece (2014, p.334), “dynamic capabilities do not operate alone. They must be coupled with effective strategizing to bring about competitive advantage.”

6.1 Theoretical Contributions

By introducing service analytics capabilities to the big data environment, we theorize the dynamic nature of such capabilities. We put forward the argument that SAC plays its role both at an operational and a dynamic level. We also assert the dynamic component of analytics capabilities, which has been largely absent in the prior literature on services marketing. Specifically, this study extends DC research in the big data context in several ways. First, the findings provide empirical support for the three primary DCs that predict SAC. Second, the findings give evidence for the notion that talent capability mediates all other capabilities in enhancing firm performance in global service industries. The paper thus delineates the boundary conditions for dynamic analytics capabilities in the data driven service economy and sheds light on the building blocks of SAC, how they are shaped and

strengthened in a firm, and their effects on firm performance. Third, SAC is a new perspective in internal marketing orientation (IMO) research and talent capability is relatively less studied. By illuminating the role of talent capability in SAC dynamics, our study extends big IMO research by providing an understanding of the roles of various capabilities in the big data environment. Specifically, the findings on the interplay between strategic alignment and talent capability provide a critical understanding of the role of companywide strategic planning in leveraging analytics insights across the service organization.

6.2 Managerial Contributions

The findings show that investment in building dynamic analytics capabilities is strategically justified in the data economy. It is worth noting that DCs transform the resource base of an organization and analytics professionals need to explore and exploit them to enhance firm performance. Managers should pay close attention to how to nurture investments, vision, culture, and talent in the changing environment. Firms that struggle with their SAC practices may be able to find gaps in their current analytics practices. For example, firms with robust technology capability may be able to sense that talent capability must be seized simultaneously to reap the full benefits of big data. Illuminating the role of talent capability, the findings show that service analytics professionals who have an analytics skillset and business knowledge can substantially enhance firm performance. Our findings lend new force to long-standing arguments for the strategic importance of internal marketing orientation (IMO), because IMO influences key decisions about talent management, incentive structures, organization structure and design, and budgeting resources to enhance talent capability through continuous training and development, thus supporting business value creation and formulating business strategy. Moreover, IMO can itself accelerate a service analytics approach. According to Fang et al. (2014, p.172), IMO refers to “the process of generating and disseminating intelligence about internal market needs and then responding to and

satisfying these needs”. Data driven service firms focus on IMO to understand market-sensing and customer-linking to enhance firm performance. Thus, cultivating analytics talent – including through the use of analytics – can help firms exploit other analytics capabilities to achieve a sustainable competitive advantage.

6.3 Limitations and Future Research Directions

Using the lens of dynamic capability and adopting reliable measures of scale items used in our research model and its robust analyses have allowed us to offer a number of unique contributions towards literature and practice. Despite this, like all other studies, some limitations and unanswered questions of our research remain and these may instigate new lines of inquiry for future studies. Firstly, our study only attempted to examine the mediating effect of talent capability and the moderating effect of firms’ strategy alignment on the link between SAC on FPER. However, exploration of other firm-level moderating factors would broaden our understanding of how SAC generates its effects on FPER. Such factors could include whether organisational culture is supportive of talent analytics as well as individual level mediating factors, for example, attitudes of top managers towards adoption and implementation of talent analytics capability. Secondly, though SAC and its underlying dimensions are context-specific due to inherent variations in the analytics industry and the availability of analytic talent, replications of our research model in other contextual settings (except for France and the USA) would augment its generalizability. Finally, to address the endogeneity problem, a future study could potentially assess the reverse causality process whereby firm performance may have an influence on the adoption and implementation of SAC.

7 Conclusion

The paper has extended understanding of service analytics capability by linking its component constructs – technology capability, information capability and talent capability – to the wider

theory of dynamic capability, examining the impact of strategy alignment, and showing how all these factors contribute to firm performance. The findings further highlight the need to recruit service analytics talent and the role of internal marketing orientation in dynamically managing this resource. Doing this successfully makes service analytics part of the dynamic, agile approach that has increasingly prompted organizations to use such capabilities to address rapid change. Specifically, the findings confirm the critical mediating role of talent capability and the moderating influence of strategic alignment to enhance and sustain service firm performance. Taken together, the paper's insights should help firms enhance performance through talent dominant service analytics capabilities in big data environment.

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FIGURES AND TABLES

Figure 1: Research Model

Table 1: Measurement Model

Dimensions	Sub-dimensions	Items	Loadings	CR	AVE
Technology Quality	Connectivity	CONN1 CONN2 CONN3	0.941 0.965 0.959	0.965	0.901
	Compatibility	COMP1 COMP2 COMP3	0.938 0.955 0.924	0.957	0.882
	Modularity	MODU1 MODU2 MODU3	0.946 0.954 0.948	0.965	0.901
	Privacy	PRIV1 PRIV2 PRIV3	0.921 0.942 0.923	0.950	0.863
Information quality	Completeness	COML1 COML2 COML3	0.933 0.942 0.871	0.939	0.838
	Currency	CURR1 CURR2 CURR3	0.947 0.937 0.931	0.957	0.881
	Format	FORM1 FORM2 FORM3	0.953 0.966 0.948	0.969	0.913
	Accuracy	ACCU1 ACCU2 ACCU3	0.915 0.870 0.940	0.934	0.825
Talent Quality	Analytics Technical knowledge	ATKN1 ATKN2 ATKN3	0.888 0.897 0.880	0.934	0.781
	Analytics management knowledge	AMKN1 AMKN2 AMKN3	0.913 0.896 0.904	0.945	0.810
	Business knowledge	BUKN1 BUKN2 BUKN3	0.915 0.935 0.940	0.937	0.840
	Relational knowledge	REKN1 REKN2 REKN3	0.896 0.908 0.879	0.937	0.788
Dynamic talent capability-strategy alignment (DTCSA)		DTCSA1 DTCSA2 DTCSA3 DTCSA4	0.902 0.909 0.948 0.939	0.969	0.855
Firm Performance (FPER)		FPER1 FPER2 FPER3 FPER4	0.895 0.897 0.910 0.903	0.945	0.812
Formative construct		Items	Weights	t-value	VIF
Control Variables (COVA)		Firm size Firm type Country	0.223 0.101 0.964	0.810 0.329 5.005	1.001 1.007 1.00

Table 2: Descriptive Statistics, Correlations, and AVEs*

<i>Construct</i>	<i>Mean</i>	<i>SD</i>	<i>CONN</i>	<i>COMP</i>	<i>MODU</i>	<i>PRIV</i>	<i>ATKN</i>	<i>AMKN</i>	<i>BUKN</i>	<i>REKN</i>	<i>COML</i>	<i>CURR</i>	<i>FORM</i>	<i>ACCU</i>	<i>DTCSA</i>	<i>FPER</i>	<i>COVA</i>
Connectivity (CONN)	5.064	1.140	0.949														
Compatibility (COMP)	4.858	1.145	0.366	0.939													
Modularity (MODU)	5.045	1.147	0.449	0.445	0.949												
Privacy (PRIV)	4.953	1.125	0.477	0.542	0.329	0.929											
Analytics Technical knowledge (ATKN)	5.032	1.164	0.564	0.338	0.381	0.335	0.884										
Analytics management knowledge (AMKN)	4.988	1.146	0.563	0.389	0.384	0.325	0.347	0.900									
Business knowledge (BUKN)	5.018	1.143	0.501	0.379	0.429	0.331	0.482	0.484	0.917								
Relational knowledge (REKN)	5.020	1.109	0.572	0.346	0.400	0.322	0.468	0.468	0.513	0.888							
Completeness (COML)	4.772	1.176	0.566	0.380	0.455	0.366	0.338	0.389	0.479	0.421	0.915						
Currency (CURR)			0.573	0.325	0.419	0.433	0.414	0.413	0.429	0.470	0.444	0.938					
Format (FORM)	5.073	1.127	0.510	0.346	0.380	0.428	0.367	0.489	0.505	0.401	0.414	0.415	0.955				
Accuracy (ACCU)	4.997	1.047	0.495	0.393	0.349	0.481	0.412	0.407	0.549	0.648	0.493	0.401	0.420	0.909			
Dynamic talent capability and strategic alignment (DTCSA)	4.951	1.028	0.109	0.025	0.097	0.025	-0.041	-0.057	-0.019	-0.094	0.025	0.080	0.065	-0.004	0.925		
Firm Performance (FPER)	n.a.	n.a.	0.573	0.609	0.617	0.528	0.559	0.569	0.590	0.575	0.587	0.58`	0.579	0.544	0.200	0.901	
Control Variables (COVA)	n.a.	n.a.	-0.081	-0.123	-0.098	-0.088	-0.082	-0.130	-0.020	-0.115	-0.198	-0.117	-0.165	-0.129	-0.132	-0.187	n.a.

*square root of AVE on the diagonal

Akter, S., Wamba, F.S., Barrett, M., Biswas, K. (2017). How talent capability can shape big data analytics capability in the big data environment? *Journal of Strategic Marketing* (In Press).

Table 3. Higher-order Model

Second-order Formative constructs	Relationships with first-order dimensions	β	t-stat
Technology capability (TECCAP)	Connectivity Compatibility Modularity Privacy	0.913 0.870 0.888 0.858	83.713 45.871 61.715 38.542
Talent capability (TALCAP)	Analytics mgmt. Knowledge Analytics tech. knowledge Business knowledge Relational knowledge	0.922 0.926 0.921 0.914	85.044 106.712 82.344 74.966
Information capability (INFCAP)	Completeness Currency Format Accuracy	0.863 0.872 0.900 0.882	47.936 51.435 76.394 56.067

Table 4: Results of the Structural Model

Main Model	Path coefficients	Standard error	t-statistic	R^2	f^2
TECCAP $\longrightarrow$ FPER	0.327	0.090	3.638	TAL.CAP = 0.608 FPER= 0.508	n.a.
TECCAP $\longrightarrow$ TALCAP	0.317	0.056	5.706		
INFCAP $\longrightarrow$ TALCAP	0.513	0.061	8.482		
INFCAP $\longrightarrow$ FPER	0.254	0.095	2.676		
TALCAP $\longrightarrow$ FPER	0.203	0.073	2.775		
INTERACTION MODEL	Path coefficients	Standard error	t-statistic	R^2	f^2
TALCAP* $\longrightarrow$ FPER DTCSA	0.153	0.080	1.919	0.582	0.177
Control Model	Path coefficients	Standard error	t-statistic	R^2	f^2
COVA $\longrightarrow$ FPER	0.092	0.049	1.866	0.516	0.016

Appendix 1: Survey Measures

2nd-order constructs	Type	1st-order constructs	Type	Item labels	Items	Sources
Dynamic Information Capability	Molecular	Completeness	Reflective	BDAPL1	The service analytics used: _____ provide a complete set of information.	(Nelson, Todd, and Wixom 2005)
			Reflective	BDAPL2	_____ produce comprehensive information.	
			Reflective	BDAPL3	_____ provide all the information needed.	
		Currency	Reflective	BDAID1	The service analytics used: _____ provide the most recent information.	(Nelson, Todd, and Wixom 2005)
			Reflective	BDAID2	_____ produce the most current information.	
			Reflective	BDAID3	_____ always provide up-to-date information.	
		Format	Reflective	SACO1	The information provided by the service analytics is _____ well formatted.	(Nelson, Todd, and Wixom 2005)
			Reflective	SACO2	The information provided by the service analytics is _____ well laid out.	
			Reflective	SACO3	The information provided by the service analytics is _____ clearly presented on the screen.	
		Accuracy	Reflective	SACT1	The service analytics used: _____ produce correct information.	(Nelson, Todd, and Wixom 2005)
			Reflective	SACT2	_____ provide few errors in the information.	
			Reflective	SACT3	_____ provide accurate information.	
Dynamic technology capability	Molecular	Connectivity	Reflective	CONN1	Compared to rivals within our industry, our organization has the foremost available big data driven service analytics systems.	(Kim, Shin, and Kwon 2012)
			Reflective	CONN2	All remote, branch, and mobile offices are connected to the central office for service analytics.	
			Reflective	CONN3	Our organization utilizes open systems network mechanisms to boost service analytics connectivity.	
		Compatibility	Reflective	COMP1	Software applications can be easily transported and used across multiple analytics platforms.	(Kim, Shin, and Kwon 2012)
			Reflective	COMP2	Our user interfaces provide transparent access to all platforms and applications.	
			Reflective	COMP3	Big data Analytics-driven service insights is shared seamlessly across our organization, regardless of the location.	
		Modularity	Reflective	MODU1	Reusable software modules are widely used in new analytics model development.	

Dynamic talent capability			Reflective	MODU2	End-users utilize object-oriented tools to create their own analytics applications.	(Parasuraman, Zeithaml, and Berry 2005)
			Reflective	MODU3	Object-oriented technologies are utilized to minimize the development time for new analytics applications.	
		Privacy	Reflective	PRIV1	Our big data driven service analytics platform protects information about personal issues.	
			Reflective	PRIV2	Our b big data driven service analytics platform protects information about personal identity.	
			Reflective	PRIV3	Our big data driven service analytics platform offers a meaningful guarantee that it will not share private information.	
	Molecular	Technical Knowledge	Reflective	ATKN1	Our service analytics personnel are very capable in terms of programming skills.	(Kim, Shin, and Kwon 2012)
			Reflective	ATKN2	Our service analytics personnel are very capable in terms of managing project life cycles.	
			Reflective	ATKN3	Our service analytics personnel are very capable in the areas of data and network management and maintenance.	
			Reflective	ATKN4	Our service analytics personnel create very capable decision support systems.	
		Technology Management Knowledge	Reflective	ATMN1	Our service analytics personnel show superior understanding of technological trends.	(Tippins and Sohi 2003; Terry Anthony Byrd 2000; Kim, Shin, and Kwon 2012)
			Reflective	ATMN2	Our service analytics personnel show superior ability to learn new technologies.	
			Reflective	ATMN3	Our b service analytics personnel are very knowledgeable about the critical factors for the success of our organization.	
			Reflective	ATMN4	Our service analytics personnel are very knowledgeable about the role of business analytics as a means, not an end.	
		Business Knowledge	Reflective	BUKN1	Our service analytics personnel understand our organization's policies and plans at a very high level.	(Kim, Shin, and Kwon 2012)
			Reflective	BUKN2	Our service analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions.	
			Reflective	BUKN3	Our service analytics personnel are very knowledgeable about business functions.	
			Reflective	BUKN4	Our service analytics personnel are very knowledgeable about the business environment.	
		Relational Knowledge	Reflective	REKN1	Our service analytics personnel are very capable in terms of planning, organizing, and leading projects.	(Kim, Shin, and Kwon 2012)
			Reflective	REKN2	Our service analytics personnel are very capable in terms of planning and executing work in a collective environment.	

			Reflective	REKN3	Our service analytics personnel are very capable in terms of teaching others.	
			Reflective	REKN4	Our service analytics personnel work closely with customers and maintain productive user/client relationships.	
Dynamic talent Capability–Strategy Alignment (DTCSA)	NA	NA	Reflective	DTCSA1	The talent analytics capability aligns with the company’s mission, goals, objectives, and strategies.	(Setia and Patel 2013)
			Reflective	DTCSA2	The talent analytics capability contains quantified goals and objectives.	
			Reflective	DTCSA3	The talent analytics capability contains detailed action plans/strategies that support company direction.	
			Reflective	DTCSA4	We prioritize major talent analytics capability investments by the expected impact on business performance.	
Firm Performance	NA	NA	Reflective		Using service analytics capability in big data environemnt improved ____ during the last 3 years relative to competitors:	(Tippins and Sohi 2003)
				FPER1	____ Customer retention	
				FPER2	____ Sales growth	
				FPER3	____ Profitability	
				FPER4	____ Return on investment	