Association for Information Systems
AIS Electronic Library (AISeL)

PACIS 2017 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

Summer 7-19-2017

Effects of User IT Capabilities and Organized Big Data Analytics on Competitive Advantage

Taro Kamioka
Hitotsubashi University, t.kami@r.hit-u.ac.jp

Ryuichi Hosoya
Hitotsubashi University, hosoyaryuichi@gmail.com

Tommi Tapanainen
University of Liege, tojuta@gmail.com

Effects of User IT Capabilities and Organized Big Data Analytics on Competitive Advantage

Completed Research Paper

Taro Kamioka
Hitotsubashi University
2-1 Naka, Kunitachi, Tokyo 186-8601, Japan
t.kami@r.hit-u.ac.jp

Ryuichi Hosoya
Hitotsubashi University
2-1 Naka, Kunitachi, Tokyo 186-8601, Japan
hosoyaryuichi@gmail.com

Tommi Tapanainen
University of Liege
Place du 20 Août 7, 4000 Liège, Belgium
tojuta@gmail.com

Abstract

In the age of big data, it becomes important to develop capabilities for utilizing information technology (IT) in order to take advantage of the potential of data for business objectives. While users have received attention in many ways, we note that the capability literature has focused more on the IT supply side. We argue that user capabilities have moved to an integral position in firm competitive advantage, and call them "User IT Capabilities" (UIC). A survey was conducted to collect data from Japanese organizations, and a total valid sample of 1,170 respondents involved in big data use was extracted. The findings show the effect of UIC on the performance of big data analytics and firm competitiveness, mediated by the variable of organized big data analytics (OBDA). The direct effects are shown to be valid irrespective of company size, although the levels of UIC and OBDA are higher in larger firms.
Keywords: Big Data Analytics Capabilities, User IT Capabilities, Organized Big Data Analytics, End User Computing

Introduction

Big data analytics (BDA) has recently drawn much attention as a possible competitive factor (Mayhew 2016). Big data analytics capabilities (BDAC) are broadly considered as organizational capabilities related to BDA such as the human skills, technology management, and culture (Gupta and George 2016). Although empirical research on BDAC is still few and far between, they have reported a positive relationship between BDAC and organizational competitive advantage through contributions to decision-making, transformation of the business, sustainable business value, and innovation (Lavalle et al. 2011; Akter et al. 2016; Gupta and George 2016; Wamba et al. 2017). As using IT is a prerequisite in BDA (Goes 2014), the capability of utilizing IT is assumed to be one of the critical elements of BDAC.

In information systems (IS) research, IT capabilities have been, without doubt, a central topic (Ross et al. 1996; Feeny and Willcocks 1998). The core principles of IT capabilities seem to have remained relevant to this day; however, it can also be said that these IT capabilities have focused mostly on the IT delivery side. Discussion on IT skills on the user side, such as end-user computing (Rockart and Flannery 1983; Harrison and Rainer 1992), peaked in the 1980s; however, in the 21st century, discussion regarding them has been very limited in the academia (Ko et al. 2011; Tarafdar et al. 2012). Instead, scholars have investigated "user capability" for IT-enabled activities pertaining to business tasks (Serrano and Karahanna 2016); decision-making or business intelligence (Chen et al. 2012; Fink et al. 2016); innovation, or knowledge (Gobble 2013; Manyika et al. 2011); or marketing (Xu et al. 2016; Erevelles et al. 2016). BDAC could be understood as a basis of such user capability.

Big data demands more advanced capabilities in using IT than has been traditionally the case (Henke et al. 2016), because user activities in BDA rely far more on utilizing management and analysis tools such as database management systems, communication or knowledge-sharing tools, data-analysis software applications, etc. Despite this, the aspect of utilizing IT on the user side has not been a focal issue in either IT capabilities or user capabilities. In this paper, we emphasize user capabilities to utilize IT for business objectives as an integral competence, and call it user IT capabilities (UIC). The present research addresses the impact of UIC on BDA and firm performance.

In examining the effects of IT-related resources including BDAC to outcome variables, past IS research suggested that intermediate variables should be considered to mediate the main effect (Akter et al. 2016; Côrte-Real et al. 2016; Wamba et al. 2017). Taking into account that BDAC subsumes organizational features, we introduce organized big data analytics (OBDA) as an intermediary construct in our model, which indicates the degree to which BDA is organized. This “organized” corresponds to the state in which the activities of BDA are organizational (firm-wide), efficiently and effectively connected, and facilitated by the organization. To our knowledge, no previous studies specifically investigated such an “organized” characteristic in BDA.

The present study investigates the impact of UIC on the performance of BDA and firm competitiveness through the mediator of OBDA by using survey data from 1,170 organizations in Japan. The data was divided into larger and smaller firms, and a multiple group analysis was conducted to verify the robustness of the results across firm size. This article proceeds as follows: after a review of the theoretical background, the model and hypotheses are presented, and the methods and data collection are described. The results, conclusions, limitations, and further research suggestions follow.

Theoretical Background

IT Capabilities and Users

IT capabilities have been a subject of great interest in IS research. The definition of IT capabilities by Ross, et al. (1996) is one of the most quoted: “the ability to control IT-related costs, deliver systems when needed, and effect business objectives through IT implementations.” Drawing on the theory of RBV (resource-based view) (Wernerfelt 1984; Ray et al. 2004), the influence of IT capabilities as organizational resources have been investigated on firm performance. For example, Bharadwaj (2000) classified resources influencing competitiveness as being IT infrastructure, human IT resources, and IT-enabled intangibles. Nevo and Wade (2010) argued that there is synergy between IT assets and organizational resources. Similar results have been reported also by many other researchers (Bakos and Treacy 1986; Mata et al. 1995; Santhanam and Hartono 2003; Ravichandran and Lertwongsatien 2005).

Although a wide range of views have been presented on the nature of capabilities (Bharadwaj 2000), the emphasis has remained on the IT-delivery or the IT-operation side. Users have often been understood to be comparatively passive in receiving services delivered by the IT department, and their role was to accept, adopt or be satisfied with IT (Wixom and Todd 2005; Bailey and Pearson 1983; Melone 1990; Kettinger and Lee 1994). The phenomenon of end-user-computing (Rockart and Flannery 1983; Harrison and Rainer 1992) was one exception. It received much attention during the diffusion of visual interfaces in the 1980s and 1990s, when many empirical studies focused on the association between the factors of usefulness, ease of use, and satisfaction (for example, Doll et al. 1983; Etezadi-Amoli and Farhoomand 1996; Tarafdar et al. 2012). Recently, end-user-computing has faded into obscurity, except with respect to end-user engineering (Ko et al. 2011), and end-user activity in co-designing (Ardito et al. 2012).

Additionally, a number of developments have eroded the value of the traditional IT capabilities. For example, a controversy was raised by Carr (2003), claiming that “IT does not matter” because of its commoditization: most IT-related resources can be purchased or outsourced to IT vendor companies. It is telling that, according to Chae et al.(2014), the positive link between IT capability and firm performance was not supported any longer in the 2000s, despite having been significant in the 1990s.

Although the commoditization of traditional IT resources has continued, the role of users has not diminished (DeLone and McLean 2003; Petter et al. 2013). Indeed, user capability for performing activities for business objectives, has been investigated in a variety of ways. For example, knowledge creation and sharing by the users in an IT environment drew attention as organizational differentiating factors (Lubit 2001). Chi et al. (2010) proposed IT-enabled capabilities as a set of firm capabilities which IT brought to “enhance firms’ ability to sense their environment and respond to opportunities and threats speedily.” However, user capabilities are separated from technology capabilities, and tend to be more task-specific (Serrano and Karahanna 2016). In such user activities, the capabilities of using IT have not, however, been explicitly postulated in research models.

Big Data Analytics and its Capabilities

Although big data has no generally accepted definition, it has been often characterized by words starting with V: volume, velocity, variety, veracity, value, visualization, etc. (Sivarajah et al. 2017). Analyzing big data requires powerful IT resources or capabilities (Baesens et al. 2016). It has impact on not only technology development but also business and organization (Manyika et al. 2011), and affects future competitiveness in business productivity and technologies (Chen and Zhang 2014).

BDA (Big Data Analytics) does not only mean analyzing data, but includes organizational activities dealing with, and obtaining value from, data (Lavalle et al. 2011). It has been defined as "a holistic approach to managing, processing and analyzing the 5V data-related dimensions to create actionable ideas for delivering sustained value, measuring performance and establishing competitive advantages" (Wamba et al. 2017). Davenport (2006) emphasized the creation of an analytics culture and instilling "an organization-wide respect for measuring, testing and evaluating quantitative evidence", whereas Chen et al. (2012) highlighted the interactive aspect of an analytics culture. McAfee and Brynjolfsson (2012) pointed out five management challenges: leadership, talent management, technology, decision-making, and company culture that are crucial in utilizing big data. The organizational capability to use big data is termed BDAC (Big Data Analytics Capability). It is "a firm's ability to assemble, integrate, and deploy its big data-specific resources" (Gupta and George 2016).

Although the research on BDAC is in its infancy, several researchers have attempted to model the constructs. For example, BDAC was composed of tangible (data and technology), human (management- and technical skills), and intangible (data-driven culture and intensity of organizational learning) resources (Gupta and George 2016); knowledge assets (Côrte-Real et al. 2016); BDA-management, technology, and talent capabilities (Akter et al. 2016); data quality management (Kwon et al 2014); BDA-infrastructure flexibility, management capabilities, and personal expertise capabilities (Wamba et al. 2017); governance, culture, technology and people (Cosic et al. 2015); technological (expected benefits and technology compatibility), organizational readiness, competitive pressure, and top-management support (Chen et al. 2015). The past research reported the impact of BDAC on firm performance based on models using the RBV theory. Similar to BDAC, business intelligence (BI) capabilities have been modelled on resources such as infrastructure integration and functionality (Peters et al. 2016) and organizational or strategic capabilities (Fink et al. 2016). In the area of marketing analytics, analytics culture, analytics skills, and data & IT have been identified as antecedents of deployment capabilities (Germann et al. 2013; Kumar et al. 2013). Those examples also demonstrated positive links between the capabilities and performances or benefits.

This research focuses on the following two points in relation to prior research on BDAC. Firstly, the capabilities of using IT, explained in the previous subsection, have not been explicitly constructed on their models separately from traditional IT capabilities, although technology management, technology capabilities, and skills were included as the components of BDAC (Akter et al. 2016; Gupta and George 2016; Wamba et al. 2017); therefore, UIC (User IT Capabilities) is explicitly introduced in our model. Using IT is deemed to be a prerequisite in BDAC, and is exemplified typically in the marketing function (Yadav and Pavlou 2014). Secondly, intermediary variables were assumed to mediate the impact of BDAC on firm performances or competitive advantage such as the organizational deployment of analytics (Germann et al. 2013); analytics capability-business strategy alignment (Akter et al. 2016); organizational agility (Côrte-Real et al. 2016); and process-oriented dynamic capabilities (Wamba et al. 2017). Considering that BDA is based on organizational activities, we assume that the condition of BDA being organized could mediate between BDAC and the outcome variables.

Model and Hypotheses

Figure 1 shows our research model with eight hypotheses: H1, H2, H3, H4, H5, and H6 are labelled for direct effects; H7 and H8 for indirect effects. The theoretical background suggested a relationship between IT capabilities and BDA, however, as described in the previous section, the "user" capability for utilizing IT was not clearly identified in prior literature and has not been structurally modeled as a construct. The present research proposes the notion of User IT Capabilities (UIC), which is the ability of users to utilize IT to achieve effective business objectives, and posits it as an independent variable related to BDAC. Past literature did not model UIC explicitly, but indicated positive links between UIC-related IT resources and performances, effectiveness or competitiveness via BDAC (Gupta and George

2016; Akter et al. 2016; Wamba et al. 2017), the traditional IT capabilities (Bhatt and Grover 2005), and user capabilities (Tamm et al. 2013). Based on these links, we propose the following hypotheses:

H1: The higher the user IT capabilities, the higher the performance of big data analytics.

H3: The higher the user IT capabilities, the higher the competitive advantage.

H6: The higher the performance of big data analytics, the higher the competitive advantage.

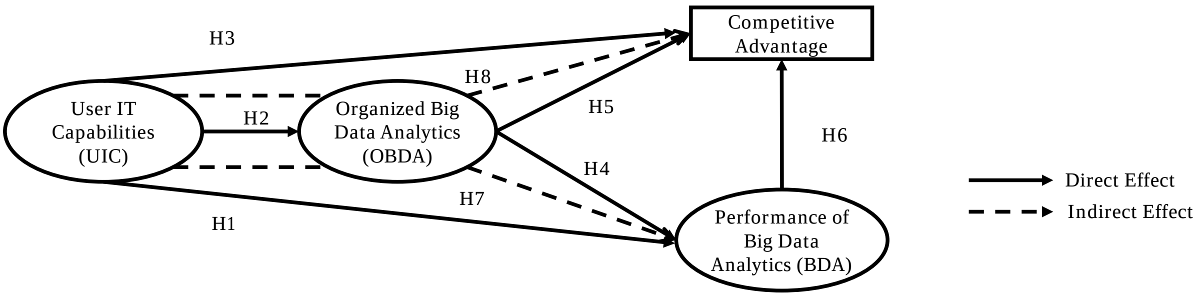


Figure 1. Conceptual Model

As described in the previous section, prior research used intermediate variables in modeling the impact of BDAC (Germann et al. 2013; Akter et al. 2016; Côrte-Real et al. 2016; Wamba et al. 2017). Considering that those variables have organizational features, we introduce a construct of organized big data analytics (OBDA), which indicates the degree that BDA is organized as a consequence of having a high BDAC. It is dependent on the following three conditions: that BDA is conducted in an organization-wide manner; that the roles and activities of units in BDA are efficiently and effectively connected and interacting; and that the activities are facilitated by the organization.

The degree to which data analytics is conducted in a well-ordered and planned way is dependent on the ability of users to plan their work around using IT or BDA tools and producing results that are potentially useful for decision-making. Such user ability to organize the activities cannot be expected if users are generally unfamiliar with BDA (Gupta & George 2016); therefore:

H2: The higher the user IT capabilities, the more organized the big data analytics.

BDAC implies a degree of organization in BDA, as organization is a facet in the definition of capability. BDAC has also been linked with performance and competitiveness. By extension, organized BDA can be likewise assumed to be related to performance and competitiveness (Côrte-Real et al. 2016; Sivarajah et al. 2017):

H4: The more organized the big data analytics, the higher the performance of big data analytics.

H5: The more organized the big data analytics, the higher the competitive advantage.

By combining H1, H2, and H4:

H7: The effect of user IT capabilities on performance of big data analytics is mediated by organized big data analytics.

By combining H2, H3, and H5:

H8: The effect of user IT capabilities on competitive advantage is mediated by organized big data analytics.

Our model utilizes mixed levels of organizational constructs. It postulates that UIC as an individual or group-level construct is linked to the other group or organization-level constructs via H1, H2, and H3. Such causal relations among the different level constructs are often seen in past research using the resource-based view, for example, in relation to IT capabilities (Bharadwaj 2000; Santhanam and Hartono 2003; Chae et al. 2014).

In addition to the above hypotheses, the present study examines the influences of firm size. The firm size effect has been often investigated in a number of IS studies (Albayrak and Gadatsch 2012; Montazemi 2006; Olutoin and Flowerday 2016).

Research Methods

The survey was commissioned by The Ministry of Internal Affairs and Communications of Japan to collect data for building a training curriculum on big data usage in "Promoting the development of advanced ICT human resources" (The Ministry of Internal Affairs and Communications of Japan 2014). A random sample of 8,745 companies was selected from the subscriber database of Nikkei Business Publications, inc., and an email was sent to the employees of companies assumed to be involved with big data. The number of respondents was 3,024, and all data was recorded anonymously.

We operationalized the variables by selecting eleven questions on a five-point Likert scale, shown in Table 1. Exploratory factor analysis was conducted to nineteen questions in the survey questionnaire; factor loadings, reliability, and validity were checked by calculating Cronbach's α, composite reliability (CR); and average variance extracted (AVE) coefficients for each factor. By considering them, the eleven questions were chosen, although they are not reported here due to space constrains. The results of CFA (Confirmatory factor analysis) are described below in this section.

The items U1, U2, and U3 refer to all the big data users from non-IS/IT divisions, e.g. business- and marketing divisions. The items O1, O2, and O3 are assumed to be reflective of OBDA. O1 is based on the concept of deployment capabilities (Germann et al. 2013; Gupta and George 2016), and refers to the degree to which data governance (Wende 2007) is established, or the leader who is responsible for big data analysis (Waterman and Bonnet 2014) is appropriately involved. O2 refers to big data management (Akter et al. 2016; Kwon et al 2014) and O3 to big data infrastructure (Peters et al. 2016; Wamba et al. 2017). The items P1, P2, and P3 refer to internal assessments of the time to collect and process data (Gupta and George 2016), as well as the sufficiency of the data. Competitive Advantages, which are related to the impact of big data analytics, are measured here using employee perceptions.

Constructs and Measurement Items	All	SME	LE		
	Avg.	Avg.	Avg.	t-test	SFL
User IT Capabilities (UIC)					
U1. Users possess high capabilities to utilize IT in BDA.	2.55	2.36	2.67	***	.90
U2. Users will proactively utilize IT in BDA.	2.78	2.60	2.90	***	.89
U3. Users take the initiative in capitalizing on big data without the support of IS division.	2.60	2.44	2.70	***	.47
Organized Big Data Analytics (OBDA)					
O1. A team or person in charge of analyzing big data takes an active part throughout the firm.	2.28	2.02	2.45	***	.87
O2. Analysis, utilization and management of big data are conducted in an organized manner.	2.28	2.06	2.43	***	.91
O3. Tools and system infrastructures for analyzing and managing big data are provided by the firm.	2.26	2.05	2.40	***	.85
Performance of Big Data Analytics					
P1. The variety of data the firm is able to collect is satisfactory.	2.75	2.74	2.76	p=.66	.68
P2. Time required to collect data is satisfactory.	2.63	2.66	2.62	p=.44	.86
P3. Time required to analyze data is satisfactory.	2.49	2.54	2.45	p=.12	.73
Competitive Advantage. Big data utilization contributes to present competitive advantage.	2.95	2.93	2.96	p=.69	
Competitive Advantage (Future). Big data utilization will contribute to competitive advantage in two years.	3.52	3.52	3.53	p=.81	

Table 1. Summary statistics and construct reliability & validity estimation

The following two criteria were used to screen the data, resulting in a total sample of 1,170 respondents:

- Currently engaged in the use, analysis, management, or decision-making related to big data; and
- Having no missing values in any of the eleven data items and firm size mentioned above.

The summary statistics are shown in Table 1. Table 2 shows the distribution of our final sample with respect to firm size. The 1,170 responses are divided by the size of 300 employees into 465 of SMEs (Small and Medium Enterprises) and 705 of LEs (Larger Enterprises). In the next section, Firm Size is given a value of 0 for SMEs and 1 for LEs.

Firm Size	Small and Medium Enterprises (n=465)			Larger Enterprises (n=705)			Total
	<20	<100	<300	<500	<1000	>=1000	
# respondents	128	285	465	555	691	479	1170

Table 2. Sample Firms by Size

CFA was performed using Amos 24. In Table 3, construct squared correlations are shown with Cronbach's α, CR, and AVE coefficients for the three constructs. They are all at either an acceptable or satisfactory level. As for reliability, Cronbach's α coefficients for UIC, OBDA, and performance of BDA exceeded the threshold value (.07) which is referred to as a satisfactory level. As for convergent validity, CR values exceeded the threshold value (.7); AVE values exceeded the threshold value (.5); and all CR values were greater than the corresponding AVE. To test the discriminant validity, we examined AVE, maximum shared variance (MSV) and average shared variance (ASV) values; obtained results (construct squared correlation is greater than AVE; AVE>0.5; AVE>MSV; AVE>ASV) demonstrated good discriminant validity.

	1	2	3	Cronbach's α	CR	AVE	MSV	ASV
1. User IT Capabilities				.858	.820	.621	.482	.286
2. Organized Big Data Analytics	.482			.906	.899	.749	.482	.307
3. Performance of Big Data Analytics	.090	.133		.796	.802	.582	.133	.112

Table 3. Construct Squared Correlations and Construct Reliability & Validity Estimation

Results

This section consists of three parts. First, the results of structural equation modeling (SEM) are given for the direct effects in Figure 1. Second, the results of multiple group analysis of the SMEs and LEs in our dataset are presented to verify the differences of direct effects by firm size. Finally, the mediation effects of OBDA in Figure 1 are shown.

Structural Equation Modeling

We conducted a SEM estimation to determine if the direct effect hypotheses in Figure 1 are supported. In addition, a control variable ('Firm Size') was introduced in order to examine the impact of firm size on each endogenous variable, namely, OBDA, Performance of BDA and Competitive Advantage. Figure 2(a) summarizes the results with the estimated coefficients and coefficients of determination. The results indicated an acceptable level of fitness of the model (χ^2 =274.959; χ^2/df =7.638, RMSEA=.075; CFI=.964; GFI=.959; AGFI=.925). An estimated direct effect of UIC on OBDA (β=.68) and that of OBDA on Performance of BDA (β=.32) were significant, thereby supporting H2 and H4. Competitive Advantage was significantly impacted both by OBDA (β=.39) and Performance of Big Data Analytics (β=.19), thus supporting H5 and H6. All the path coefficients for Firm Size are also significant (The firm size effect is described in more details in the next subsection by multiple group analysis). However, the impacts of UICs on Performance of BDA (β=.10/H1) and Competitive Advantage (β=.07/H3) were not significant.

To supplement the SEM estimation above, we re-estimated the model with the outcome variable Competitive Advantage (Future) instead of Competitive Advantage in Figure 2(a). The results are presented in Figure 2(b). Naturally, the difference is only the estimated coefficients connected to Competitive Advantage (Future) and its coefficients of determination, compared to Figure 2(a). The path coefficients of the direct paths from UICs and OBDA, respectively, to Competitive Advantage (Future) were estimated to be significant (β=.20 at p<.001 for both), while no significance was found for the one on the path from Performance of BDA to Competitive Advantage (Future). The determinant coefficient ($R^2 = .14$) for Competitive Advantage (Future) are much less than that of Competitive Advantage in the original model ($R^2 = .28$ in Figure2(a)). The same or similar estimation results were obtained for other path/determinant coefficients to those between Figure 2(a) and 2(b). The overall model fit was acceptable with fitness indices (χ^2 =260.369; χ^2/df =7.232, RMSEA=.073; CFI=.965; GFI=.961; AGFI=.929). The results suggest that UICs and OBDA contribute to the firm's competitive advantage in a longer term, while the present Performance of BDA is not necessarily linked to it.

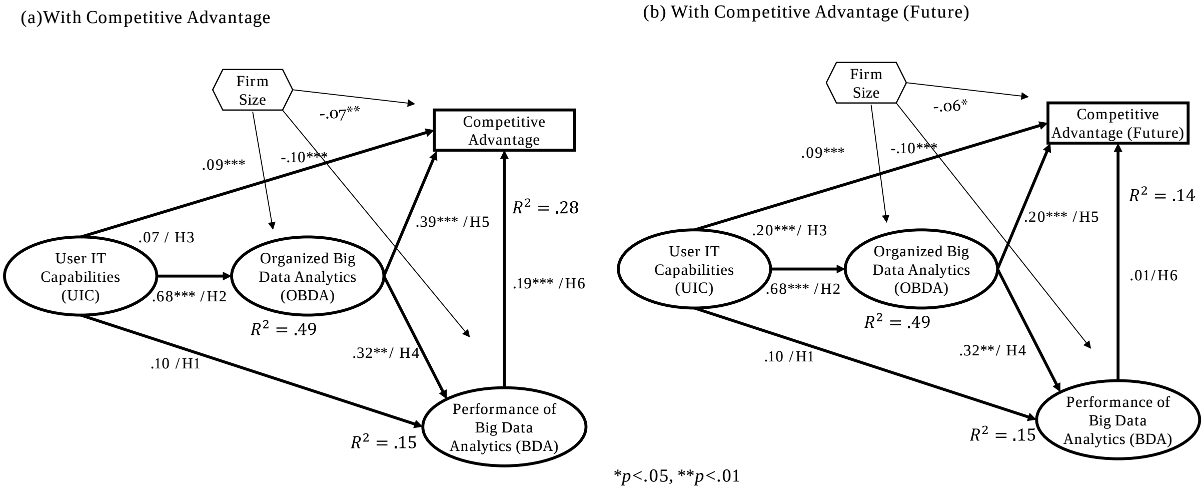


Figure 2. Structural Model with Estimation Results

Multiple Group Analysis for SMEs and LEs

As shown in Table 1, the results of t-test indicate that the scores of UIC and OBDA between small- and medium-sized enterprises (SMEs) and large enterprises (LEs) are significantly different. This subsection examines the distinctiveness of the direct effects in the two groups by conducting multiple group analysis (MGA) (Vandenberg and Lance 2000).

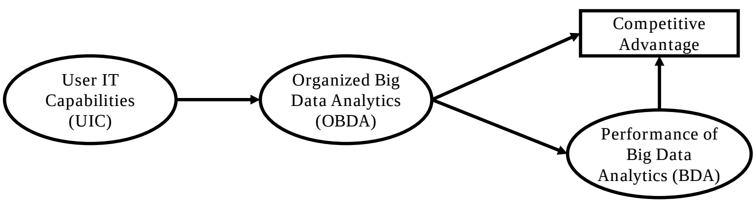


Figure 3. Structural Model for Multiple Group Analysis

The MGA model in Figure 3 is different in its configuration to the structural equation model in Figure 2(a). First, the control variable 'Firm Size' is removed since MGA incorporates the group-wise parameter estimation, eliminating the need for the control variable to dichotomize the dataset. Second, since the direct effects of UIC on Performance of BDA (H1) and on Competitive Advantage (H3) were not significant as shown in the previous subsection, we decided to remove those two paths from the model.

The MGA model was analyzed using Amos 24. Results demonstrated a good fit of the model to the dataset containing data for both SMEs and LEs (χ^2 =319.960; χ^2/df =4.848; RMSEA=.057; CFI=.961; GFI=.948; AGFI=.913). An equivalent level of model fit was preserved even when all the coefficients of the paths illustrated in Figure 3 were constrained to be equal between the two groups (configural invariance). Tests for a more constrained invariance, such as measurement invariance, failed by resulting in deteriorated fitness indices of the model, evidencing that configural invariance best described the distinctiveness between the two groups.

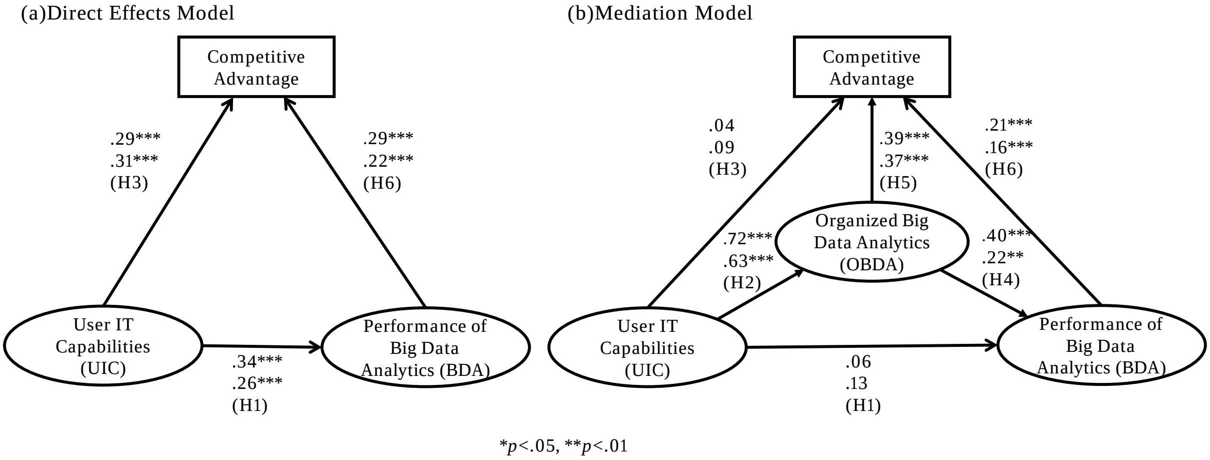
MGA yields path coefficient estimates independently for each group. Among the inter-construct path coefficients, only the one between UIC and OBDA was identified to be significantly different in SMEs and LEs (non-standardized β=.62 for SMEs and .80 for LEs; t= 2.881 for difference test). The difference in the path coefficient is .18; this is consistent with the non-standardized path coefficient .17 (the standardized one is 0.09) between the control variable 'Firm Size' and OBDA in the structural model in Figure 2(a).

In sum, the results of MGA for SMEs and LEs show that the two groups possess an identical structure as a whole which is modeled as the path diagram in Figure 3, although the inter-construct path coefficient between UIC and OBDA is significantly different in these two groups.

Mediation Analysis

In order to confirm the mediating effects of OBDA, a series of steps was taken in accordance with the mediation analysis procedure by Shrout and Bolger (2002). In accordance with the results of MGA described above, mediation analysis was conducted for SMEs and LEs separately using the same set of path diagrams by using Amos 24.

The model illustrated in Figure 4(a) was used to test the significance of the direct effects of UIC on the two dependent variables: Performance of BDA and Competitive Advantage. The estimated standardized path coefficients are shown for SMEs at the bottom and ones for LEs at the top. All the path coefficients were found to be significant, hence the significance of the direct effects corresponding to H1, H3, and H6 in Figure 2(a).



Standardized path coefficients for SMEs at the bottom and for LEs at the top.

Figure 4. Direct Effects Model and Mediation Model

Indirect Path	Indirect Effect		Lower bound of 95% confidence interval (>0 indicates the effect is significant)	
	SME	LE	SME	LE
User IT Capabilities →Performance of Big Data Analytics	.142	.293	.053	.196
User IT Capabilities →Competitive Advantage	.277	.357	.202	.278

Table 4. Indirect Effects Estimation

Subsequently, mediation analysis of the indirect effects of UIC on the dependent variables mediated by OBDA was conducted using the model in Figure 4(b). In association with H7 and H8 in Figure 1, the indirect effects of UIC on Performance of BDA and Competitive Advantage, which are mediated by OBDA, are tested with the bootstrap method. Table 4 shows the estimates of indirect effects of UIC and lower bounds of the bootstrap confidence interval based on a bootstrap sample of specified size 2,000. All the lower bounds are above zero, indicating significance of all the estimated indirect effects.

The path coefficients between UIC and Performance of BDA and between UIC and Competitive Advantage, respectively, are no longer significant in the mediation model, while all the direct paths to OBDA exhibit significant path coefficients, hence demonstrating full mediation by OBDA. The mediating effects of OBDA on UIC holds in two ways: one towards Performance of BDA and the other towards Competitive Advantage, supporting H7 and H8, respectively.

Conclusion, Limitations, and Future Research

There is an increasing demand for organizational capabilities to take advantage of big data (Baesens et al. 2016), and using IT for big data analytics (BDA) is one prerequisite for these capabilities. While big data analytics capability (BDAC) has been linked with firm performance and competitive advantage (Akter et al. 2016; Gupta and George 2016; Wamba et al. 2017), it is not yet well understood what kind of IT capabilities users require to produce organizational outcomes using big data, and whether such capabilities are linked to competitive advantage. Prior research has proposed “user capabilities” based on utilizing IT such as the extraction and communication of information (Lubit 2001, Serrano and Karahanna 2016); however, capabilities related to utilizing IT have not been clearly discussed separately from the user capabilities. The research on big data analytics capability has not elaborated user IT capability (UIC). Therefore, in this research, we specifically address UIC with respect to big data, and emphasize more elementary dimensions of this capability, namely, proactivity and initiative in utilizing IT.

This research validated a structural model which indicated that UIC has a positive relationship with the performance of BDA and competitive advantage, mediated by the condition that BDA is organized. The model applies regardless of firm size. In addition, both structural and quantitative distinctiveness of small and medium enterprises (SME) and larger firms were examined by multiple group analysis. The results demonstrated that the causal structure consisting of the three constructs and one outcome variable (as illustrated in Figure 1) can be applied both to SMEs and larger firms; the major difference between the two groups lies in the impact of UIC on organized big data analytics (OBDA), where UIC’s impact is higher with larger firms by .18 (average) on the five-point Likert scale. A larger firm tends to have more difficulties in organizing firm-wide BDA-related activities; they should depend more on their UIC to facilitate OBDA through utilizing IT in, for example, sharing information, communicating and decision-making. Interestingly, this increased impact of UIC is offset by the decreased impact of OBDA on performance of BDA and competitive advantage. This offsetting effect can be confirmed by the SEM estimation results (shown in Figure 2(a)) with the inversed signs of the path coefficients associated with the control variable ‘Firm Size.’ The offsetting effect corresponds with the summary statistics in Table 1, where no significant differences are found between the two groups in the means of measurement items for performance of BDA and competitive advantage, while the means of the other measurement items are significantly higher in larger firms. These results provide the following implications: 1) The structural model discussed in the present study is valid for a firm of any size, and 2) A larger firm may need a different approach such as IT governance or data governance (Wende 2007) in order to maintain higher levels of UIC and OBDA in ordered to achieve an equivalent level of Performance of BDA and Competitive Advantage to those of a smaller firm.

The intermediary role of OBDA was confirmed through mediation analysis. From the analysis results, it is suggested that OBDA is a key to effectively associate user IT capabilities to big data utilization activities taking place at the user side. The results of the supplementary analysis with the estimation of future competitive advantage suggested that OBDA, once it is achieved within a firm, would become a valuable resource that contributes to a sustainable competitive advantage of the firm while an increase in the performance of BDA alone would only have a temporary effect on competitive advantage.

There are limitations to our study to be considered. First, as the academic community is yet in a preliminary stage of modeling UIC and OBDA, it is recommended that the linkages found are investigated also with alternative conceptualizations of UIC and OBDA. Secondly, the measurement of performance and competitive advantage was based on subjective perceptions.

Future research is suggested on the following three points. Firstly, it is useful to refine the conceptual model adopted in this research by building on second- or higher-order constructs for UIC and OBDA with richer data items. In this study, UIC is modelled in the domain of big data analytics. However, there is room to argue as to whether UIC should be conceptualized as a general capability independent of BDAC, or as a domain-specific capability in BDAC. On the other hand, BDAC could be modeled as a sub-concept in traditional IT capabilities, or as an independent concept. As for OBDA, it is modelled here as a dependent variable of UIC and an intermediary construct between UIC and its performance. Prior research noted other organizational factors having similar effects, including organizational structure (Krishnamoorthi and Mathew 2015), data governance (Wende 2007; Kamioka et al. 2016), and deployment of analytics (Germann et al. 2013). These factors should be taken into account in future research. Secondly, more behavioral and financial outcomes of BDA should be added in the measurement of performance and competitive advantage. Thirdly, the role of executives such as the Chief Digital or Data Officer has been emphasized in order to strengthen organizations' capabilities in the dynamically changing digital world (Hughes 2015; Tyler et. Al. 2016), and future research should explore how the actions of these executives influences OBDA.

Acknowledgements

We thank the ICT Accessibility and Human Resources Development Division of the Information and Communications Bureau in the Japan Ministry of Internal Affairs and Communications, for giving us access to the nationwide survey used as the basis of this research. We also acknowledge the valuable support of the European Commission, which supported one of the authors during this research.

References

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., and Childe, S. J. 2016. "How to Improve Firm Performance Using Big Sata Analytics Capability and Business Strategy Alignment?" *International Journal of Production Economics* (182), pp.113-131.

Ardito, C., Buono, P., Costabile, M. F., Lanzilotti, R., and Piccinno, A. 2012. "End Users as Co-designers of their Own Tools and Products," *Journal of Visual Languages and Computing* (23:2), pp.78–90.

Albayrak, A. C., and Gadatsch, A. 2012. "IT Governance model for small and medium sized enterprises,"in Proceedings of the 9th European, Mediterranean and Middle East Conference on Information Systems, Munich, European, pp. 380-390.

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., and Zhao, J. L. 2016. "Transformational Issues of Big Data and Analytics in Networked Business," MIS Quarterly (40:4), pp. 807-818.

Bailey, J. E. and Pearson, S. W. 1983. "Development of a Tool for Measuring and Analyzing Computer User Satisfaction," *Management Science* (29:5), pp. 530-545.

Bakos, J. Y., and Treacy, M. E. 1986. "Information Technology and Corporate Strategy: A research perspective," *MIS Quarterly: Management Information Systems* (*10*:2), pp.107-119.

Bharadwaj, A. S. 2000. "A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation," *MIS Quarterly: Management Information Systems* (*24*:1), pp. 169-193.

Bhatt, G. D., and Grover, V. 2005. "Types of Information Technology Capabilities and Their Role in Competitive Advantage: An Empirical Study," *Journal of Management Information Systems* (22:2), pp. 253-277.

Carr, N. G. 2003. "IT Does Not Matter," *Harvard Business School*, June,pp. 5-12.

Chae, H., Koh, C., and Prybutok, V. 2014. "Information Technology Capability and Firm Performance: Contradictory Findings and Their Possible Causes," *MIS Quarterly* (*38*:1), pp. 305-326.

Chen, C. L. P., and Zhang, C. Y. 2014. "Data-Intensive Applications, Challenges, Techniques and Technologies: A Survey on Big Data," *Information Sciences* (*275)*, pp. 314-347.

Chen, D. Q., Preston, D. S., and Swink, M. 2015. "How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management," *Journal of Management Information Systems* (*32*:4), pp. 4-39.

Chen, H., Chiang, R. H. L. and Storey, V. C. 2012. "Business Intelligence and Analytics: From Big Data to Big Impact," MIS Quarterly (36:4), pp. 1165-1188.

Chi, L., Ravichandran, T., and Andrevski, G. 2010. "Information Technology, Network Structure, and Competitive Action," *Information Systems Research*, (*21*:3), pp. 543-570.

Côrte-Real, N., Oliveira, T., and Ruivo, P. 2016. "Assessing Business Value of Big Data Analytics in European Firms," *Journal of Business Research* (*70)*, pp. 379-390.

Cosic, R., Shanks, G., and Maynard, S. 2015. "A business Analytics Capability Framework," *Australasian Journ*al of Information Systems (19), pp. S5-S19.

Davenport, T. H. 2006. “Competing on Analytics, ”Harvard Business Review (84:1), pp. 98.
DeLone, W. H., and McLean, E. R. 2003. “Journal of Management Information Systems the DeLone and McLean Model of Information Systems Success: A Ten-Year Update,” *Journal of Management Information Systems* (*19*:4), pp. 9-30.
Doll, W. J., and Torkzadeh, G. 1983. “The Measurement of End-User Computing Satisfaction,” *MIS Quarterly* (*12*:2), pp. 259-274.
Erevelles, S., Fukawa, N., and Swayne, L. 2016. “Big Data Consumer Analytics and the Transformation of Marketing,” *Journal of Business Research* (*69*:2), pp. 897-904.
Etezadi-Amoli, J., and Farhoomand, A. F. 1996. “A Structural Model of End Eser Computing Satisfaction and User Performance,” *Information and Management* (*30*:2), pp.65-73.
Feeny, D. F., and Willcocks, L. P. 1998. “Core IS Capabilities for Exploiting Information Technology,” *MIT Sloan Management Review* (*39)*, pp. 9-21.
Fink, L., Yogev, N., and Even, A. 2016. “Business Intelligence and Organizational Learning: An Empirical Investigation of Value Creation Processes,” *Information and Management* (*54*:1), pp. 38-56.
Germann, F., Lilien, G. L., and Rangaswamy, A. 2013. “Performance Implications of Deploying Marketing Analytics,” *International Journal of Research in Marketing* (*30*:2), pp. 114-128.
Gobble, M. M. 2013. “Big Data: The Next Big Thing in Innovation,” *Research Technology Management* (*56*:1), pp. 64-66.
Goes, P. B. 2014. “Big Data and IS Research,” *MIS Quarterly* (*38*:3), pp. iii-viii.
Gupta, M., and George, J. F. 2016. “Toward the Development of a Big Data Analytics Capability,” *Information and Management* (*53*:8), pp. 1049-1064.
Harrison, A. W., and Rainer Jr, R. K. 1992. “The Influence of Individual Differences on Skill in End-User computing,” *Journal of Management Information Systems* (*9*:1), pp. 93-111.
Henke, N., Libarikian, A., and Wiseman, B. 2016. “Straight Talk About Big Data,” *McKinsey and Company* ,August, pp.1–13.
Hughes, P. 2015. "The rise of the Chief Digital Officer," Deloitte Digital.
Kamioka, T., Luo, X., and Tapanainen, T. (2016). “An Empirical Investigation of Data Governance: The Role of Accountabilities,” in *Proceeding of the 20th Pacific Asia Conference on Information Systems*, Chiayi, Taiwan.
Kettinger, W., and Lee, C. 1994. “Perceived Service Quality and User Satisfaction with the Information Services Function,” *Decision Sciences* (*25*:5-6), pp. 737-766.
Ko, A. J., Abraham, R., Beckwith, L., Blackwell, A., and Burnett, M. 2011. “The State of the Art in End-User Software Engineering,” *ACM Computing Surveys* (*43*:3), pp. 1-44.
Krishnamoorthi, S., and Mathew, S. K. 2015. "Business Analytics and Business Value : A Case Study," in *Proceedings of the 36th International Conference on Information Systems*, Ft. Worth, Texas, USA, pp. 1-17.
Kumar, V., Chattaraman, V., Neghina, C., Skiera, B., Aksoy, L., Buoye, A., and Henseler, J. 2013. “Data-Driven Services Marketing in a Connected World,” *Journal of Service Management* (24:3), pp. 330-352.
Kwon, O., Lee, N., and Shin, B. 2014. “Data Quality Management, Data Usage Experience and Acquisition Intention of Big Data Analytics,” *International Journal of Information Management* (34:3), pp. 387-394.
Lavalle, S., Lesser, E., Shockley, R., Hopkins, M. S., and Kruschwitz, N. 2011. “Big Data, Analytics and the Path from Insights to Value,” *MIT Sloan Management Review* (52:2), pp. 21-32.
Lubit, R. O. Y. 2001. “Tacit Kowledge and Knowledge Management: the Keys to Sustainable Competitive Advantage,” *Organizational Dynamics* (*29*:4), pp. 164-178.
Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., and Byers, A. H. 2011. “Big Data: The Next Frontier for Innovation, Competition, and Productivity,” *McKinsey Global Institute* ,June, pp. 156.
Mata, F. J., Fuerst, W. L., and Barney, J. B. 1995. “Information Technology and Sustained Competitive Advantage,” *MIS Quarterly* (19),December, pp. 487-505.
Mayhew, H., Saleh, T., and Williams, S. 2016. “Making Data Analytics Work for You- Instead of the Other Way Around,” *McKinsey Quarterly* ,October, pp. 1-15.
McAfee, A., and Brynjolfsson, E. 2012. “Big Data. The Management Revolution,” *Harvard Buiness Review* (90:10), pp. 61-68.
Melone N P. 1990. “A Theoretical Assessment of the User-Satisfaction Construct in Information Systems Research,” *Management Science* (36:1), pp. 76-91.
Montazemi, A. R. 2006. “How They Manage IT: SMEs in Canada and the US,” *Communications of the ACM* (*49*:12), pp. 109-112.

Nevo, S., and Wade, M. R. 2010. "The Formation and Value of IT-Enabled Resources: Antecedents and Consequences of Synergistic Relationships," *MIS Quarterly* (34:1), pp. 163-183.
Olutoyin, O., and Flowerday, S. 2016. "Successful IT Governance in SMES : An Application of the Technology - Organization - Environment Theory," *South African Journal of Information Management*, pp. 1-8.
Peters, M. D., Wieder, B., Sutton, S. G., and Wakefield, J. 2016. "Business Intelligence Systems Use in Performance Measurement Capabilities: Implications for Enhanced Competitive Advantage," *International Journal of Accounting Information Systems* (21), pp. 1-17.
Petter, S., DeLone, W. D., and McLean, E. R. 2013. "Information Systems Success: The Quest for the Independent Variables," *Journal of Management Information Systems* (*29*:4), pp. 7.
Ravichandran, T., and Lertwongsatien, C. 2005. "Effect of Information Systems Resources and Capabilities on Firm Performance: A Resource-Based Perspective," *Journal of Management Information Systems* (*21*:4), pp. 237-276.
Ray, G., Barney, J. B., and Muhanna, W. A. 2004. "Capabilities, Business Processes, and Competitive Advantage: Choosing the Dependent Variable in Empirical Tests of the Resource-Based View," *Strategic Management Journal* (*25*:1), pp. 23-37.
Rockart, J., and Flannery, L. 1983. "The Management of End-User Computing," *Communications of the ACM* (*26*:10), pp. 776-784.
Ross, J. W., Beath, C. M., and Goodhue, D. L. 1996. "Develop Long-Term Competitiveness through IT Asset," *MIT Sloan Management Review* (38:1), pp. 31.
Santhanam, R., and Hartono, E. 2003. "Issues in Linking Information Technology Capability to Firm Performance," *MIS Quarterly* (*27*:1), pp. 125-153.
Serrano, C., and Karahanna, E. 2016. "The Compensatory Interaction between User Capabilities and Technology Capabilities in Influencing Task Performance: An Empirical Assessment in Telemedicine Consultations," *MIS Quarterly* (40:3), pp. 597-621.
Shrout, P. E., and Bolger, N. 2002. "Mediation in Experimental and Nonexperimental Studies: New Procedures and Recommendations," *Psychological methods* (7:4), pp. 422.
Sivarajah, U., Kamal, M. M., Irani, Z., and Weerakkody, V. 2017. "Critical Analysis of Big Data Challenges and Analytical Methods," *Journal of Business Research* (*70*), pp. 263-286.
Tamm, T. T., Seddon, P., and Shanks, G. 2013. "Pathways to Value from Business Analytics," in *Proceedings of the 34th International Conference on Information Systems*, Milan, Italy, pp. 2915-2930.
Tarafdar, M., Tu, Q., and Ragu-Nathan, T. S. 2012. "Impact of Technostress on End-User Satisfaction and Performance," *Journal of Management Information Systems* (*27*:3), pp. 303-334.
The Ministry of Internal Affairs and Communications of Japan (2014a)., available at http://www.soumu.go.jp/johotsusintokei/whitepaper/ja/h24/html/nc121410.html, in Japanese.
Tyler, B., Abercrombie, C., and Shockley, R. 2016. "The Chief Data Officer playbook," IBM Institute for Business Value.
Vandenberg, R. J., and Lance, C. E. 2000. "A Review and Synthesis of the Measurement Invariance Literature: Suggestions, Practices, and Recommendations for Organizational Research," Organizational Research Methods (3:1), pp. 4-70.
Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., and Childe, S. J. 2017. "Big Data Analytics and Firm Performance: Effects of Dynamic Capabilities," *Journal of Business Research* (*70)*, pp. 356-365.
Wende, K. 2007. "A Model for Data Governance-Organising Accountabilities for Data Quality Management," in *Proceedings of the 18th Australasian Conference on Information Systems,* Toowoomba, Queensland, pp. 417-425.
Wernerfelt, B. 1984. "A Resource Based View of the Firm," *Strategic Management Journal* (*5*:2), pp. 171-180.
Westerman, G., and Bonnet, D. 2014. "Leading Digital: Turning Technology into Business Transformation," Harvard Business Review Press.
Wixom, B. H., and Todd, P. A. 2005. "A Theoretical Integration of User Satisfaction and Technology Acceptance," *Information Systems Research* (*16*:1), pp. 85-102.
Xu, Z., Frankwick, G. L., and Ramirez, E. 2016, "Effects of Big Data Analytics and Traditional Marketing Analytics on New Product Success: A Knowledge Fusion Perspective," *Journal of Business Research* (*69*:5), pp. 1562–1566.
Yadav, M. S., and Pavlou, P. A. 2014. "Marketing in Computer-Mediated Environments: Research Synthesis and New Directions," *Journal of Marketing* (*78*:1), pp. 20-40.