Journal of Global Information Management
Volume 29 • Issue 4 • July-August 2021

Value Chain Creation in Business Analytics

Dong Yoo, Virginia State University, USA
James J. Roh, Rowan University, USA

ABSTRACT

Firms are awash in big data and analytical technology as part of the process of deriving values in the current turbulent environment. The literature has reached a consensus that investments in technology only may not reap benefits from business analytics (BA). As such, the main purpose of BA is not about how to install technical capabilities, but about how to create a process whereby a firm builds a value chain converting data into insights and ultimately into quality outcomes. Drawing upon the theory of the information value chain, this study develops a BA value chain creation model and tests it with 268 firms. Results show that organizational resilience, absorptive capacity, and analytical IT capabilities are critical antecedents of analytical decision-making quality, which in turn influences BA net benefits. In particular, organizational resilience emerges as a more significant determinant of analytical decision-making quality than technology and people in the BA value chain creation. Theoretical and practical implications are also discussed in this paper.

KEYWORDS

Absorptive Capacity, BA Outcomes, BA Value Chain Model, Business Analytics, Organizational Resilience

INTRODUCTION

Business analytics (BA) has emerged with the premise that data-driven decision-making will lead firms to sustain competitive advantage (Abbasi et al., 2016; Seddon et al., 2017). Envisioning a better future, organizations have invested more resources in BA to cope with constant demands for innovation. In following the course of action, firms have reached a consensus that investments in information technology (IT) alone cannot result in expected benefits (Gupta & George, 2016; Joseph et al., 2017). As the success of BA does not dwell on building technical capabilities only, it is required to aim to create a scheme whereby a firm embeds value chain creation, converting data into relevant information and, ultimately, into knowledge for effective action. This process is called value chain creation in BA, defined here as a series of activities by which a firm makes good decisions to deliver valuable products or services.

DOI: 10.4018/JGIM.20210701.oa6

The theory of the information value chain provides a theoretical foundation for this study. It is described as "the cyclical set of activities necessary to convert data into information, and subsequently, to transform information into knowledge … which individuals use to make decisions and take actions. The decisions and actions then result in outcomes such as business value and additional data" (Abbasi et al., 2016, p. iii). The theory also contends that the intertwined interaction of technology, people, and organizational context plays a significant role in the value creation. Drawing upon the theory, this study investigates the impact of organizational resilience, absorptive capacity, and analytical IT capabilities on BA value chain creation. Although the theory suggests the interdependence of technology, people, and organizational context, the literature awaits more studies that holistically integrate those crucial components and relate them to BA outcomes. This study fills the research gap in the field of BA, and refined research questions are as follows:

RQ1: What is the role of organizational resilience and how does it turn BA into meaningful outcomes in decision-making and analytical benefits?
RQ2: What is the role of absorptive capacity in the BA value chain model and how do analytical IT capabilities enhance absorptive capacity?
RQ3: When it comes to BA outcomes, how can the pillars of BA (i.e., IT, people, and organizational context) translate into analytical decision-making and net benefits in value chain creation?

By addressing the research questions, this paper makes novel contributions to the literature. First, this study explores organizational resilience in BA value chain creation. The literature acknowledges that organizational aspects play a pivotal role in the BA chain model and help realize the full potential of BA (Abbasi et al., 2016). Strategic, operational decisions are increasingly supported by BA, and a proper organizational climate needs to be understood for effective value creation through BA. In particular, organizational resilience is a firm's ability to face adverse circumstances and transform them into opportunities (Ambulkar et al., 2015). Despite its growing significance and relevance, there are few studies on organizational resilience in the context of BA.

Second, this study illustrates the role of absorptive capacity in the BA value chain creation. Value chain studies suggest that technical capability cannot generate intended value by itself; it needs to be accompanied by proper dynamics (Drnevich & Croson, 2013). In other words, BA tools generate reports through sophisticated techniques, but we contend that the technology should be aligned with a firm's capability to identify valuable knowledge, assimilate it into their decision-making loop, and apply it for innovation (Iyengar et al., 2015). To the best of our knowledge, this theoretical link to absorptive capacity has not been adequately investigated in the context of BA.

Third, this study examines how desired outcomes can be derived in the value chain creation. A recent survey of Fortune 1,000 C-level executives reports that firms do not see big returns from their investments in big data (NewVantage Partners, 2017) while some reap positive outcomes (Krishnamoorthi & Mathew, 2018). As these mixed results call for more inquiries, we argue that BA's desired outcomes result from achieving congruence among organizational structure, IT, and human agency. Furthermore, we theoretically and empirically examine how a firm can generate desired outcomes via BA value chain creation.

THEORETICAL FOUNDATIONS

The theory of the information value chain contends that firms should have a proper mechanism to facilitate data-to-decision dynamics. It adds that the various source of data needs to be interconnected in a timely and accurate manner, and that the routine of decision-making needs to be empowered with accurate information and useful insights in a responsive manner (Abbasi et al., 2016). Data-to-decision dynamics also involves the interplay among people, organizational context, and technology, and their

seamless integration implies effective value creation. As such, the theory offers useful theoretical explanations for how a firm can utilize BA to arrive at effective performance.

Anecdotal evidence has shown that BA can be successfully implemented when it is supported by data quality, IT capabilities, organizations, and human capital (Gupta & George, 2016; Seddon et al., 2017). Little attention has been paid in the literature, however, to organizational resilience and absorptive capacity, along with their interrelationships with BA technical capabilities and firm performance. Organizational resilience is critical in coping with disruptions in a hypercompetitive environment, and it also highlights the element of organizational context in the information value chain. Additionally, studies consistently argue that creative work such as "sense-making, framing, understanding and deciding," despite all of the technical advances, is done by people (Seddon et al., 2017). Therefore, it is worth making adequate theoretical connections among organizational resilience, analytical IT capabilities, absorptive capacity, and BA performance.

Organizational Resilience in BA Value Chain Creation

A firm's resilience, translating organizational adversity into opportunities, is essential as firms face challenges in fast-paced circumstances (Annarelli & Nonino, 2016; Su & Linderman, 2016). Viewed resilience as an ability to bounce back from a shock and recover the original shape, the literature conceptualizes organizational resilience as a capability that responds to unfamiliar, challenging situations, develops appropriate responses, and transforms disruptive shocks into opportunities for growth (Ambulkar et al., 2015; Park et al., 2015). The construct's dimensions have been presented in various ways, as shown in Table 1. For instance, a study reports that organizational resilience consists of cognitive, behavioral, and contextual dimensions (Lengnick-Hall et al., 2011). Another study illuminates the concept as forward-looking leadership, open organizational culture, strategic planning, and innovation (de Oliveira Teixeira & Werther, 2013), while others regard it with sensing weak signals and responding to those signals (Su & Linderman, 2016). Differing dimensions have been employed based on each study's context, and this study identifies strategic vision salience, problem-solving capability, innovativeness, and resource access efficiency as dimensions of organizational resilience in the BA context. The rationale for this conceptualization is explained in the following sections.

Strategic Vision Salience

A firm's vision is a practical guide to setting goals, making decisions, and keeping the organization together by creating a mental picture of the future. Vision is described as a vivid, idealized portrait of what the organization aspires to be someday (Carton et al., 2015; de Oliveira Teixeira & Werther, 2013), and vision salience indicates the extent to which an organization is clearly aware of a shared sense of the firm's purpose and ultimate goals. With a vision guiding commitment and cohesion, salient vision enables an organization to embrace opportunities and threats and to make differences during times of transition or turbulence. Salient vision encourages organizational members to find meanings and purposes rather than to become rigid and dysfunctional when disruptions occur (Lengnick-Hall et al., 2011). A high sense of cohesiveness via vision salience promotes a clear picture of the firm's future and puts it into practice with resilience (Zook, 2016).

Problem-Solving Capability

Turbulence may present unprecedented problems for an organization, and it is often unstructured and open-ended (Althuizen & Reichel, 2016). In such disruptive circumstances, a firm's capability to solve problems can determine the fate of an organization. Problem-solving capability is defined as a firm's ability to make sense of issues, develop feasible solutions swiftly, and solve problems meaningfully (Su & Linderman, 2016). Disruptions demand proper attention to the problems, and effective responses are directly associated with a firm's survival and renewal (Figl & Recker, 2016). Firms with problem-solving capability surmount challenges and renew competitive advantage by

Table 1. Summary of prior research on organizational resilience

Author(s)	Research Context	Definition	Dimensions	Level/Method
Lengnick-Hall et al. (2011)	Human Resource Management	A firm's ability to effectively absorb, develop situation-specific responses to, and ultimately engage in transformative activities to capitalize on disruptive surprises that potentially threaten organization survival	(1) Cognitive dimension: a strong sense of purpose, a genuine vision, constructive sense making (2) Behavioral dimension: unconventional responses, repetitive routines, preventive actions, interpersonal interactions, information sharing, and power sharing (3) Contextual dimension: psychological safety, deep social capital, diffused power and accountability, resource networks	Conceptual Paper
de Oliveira Teixeira & Werther (2013)	Competitive Advantages	The competency to continuously develop or renew companies' configuration of intellectual, financial, technological, human, and other resources	(1) Forward-looking leadership; (2) Open organizational culture; (3) Strategic planning; (4) Making innovation a way of life	Organizational Level/Case Studies
Ambulkar et al. (2015)	Supply Chain Management	The capability of the firm to be alert to, adapt to, and quickly respond to changes brought by a supply chain disruption	Scales: Ability to cope with changes; ability to adapt to the disruption; ability to provide a quick response; ability to maintain high situational awareness	Organizational Level/199 US Manufacturing Data

assessing problems, organizing resources, and providing solutions. Resilient organizations via problem-solving capabilities can deal with uncertainties where firms need to face constantly.

Innovativeness

A hallmark of organizational resilience is innovativeness as disruptions often accompany daunting challenges and make competitive advantage irrelevant (de Oliveira Teixeira & Werther, 2013). Firms can fall behind due to cliché-ridden approaches and groupthink from previous accomplishments and acceptance of the status quo. In other words, stagnant firms fail to seize opportunities provided by changes in the market. Striving for forward-thinking and ground-breaking ways to achieve renewal, resilient firms, however, refuse to yield to abrupt flight, and they develop unconventional approaches to combating threats. It is the innovativeness-encouraging atmosphere that organizational members feel motivated to make suggestions for new opportunities and to take risks even if their endeavors may turn out to be failures. Such firms are constantly on the search for novel processes, technologies, and methods to rise up from adversity (Su & Linderman, 2016).

Resource Access Efficiency

Resource access has been well known as a critical aspect of organizational effectiveness (Ayabakan et al., 2017). Enthusiastic and lively organizations harbor a system conducive to locating various

resources including financial, human, and technical support. The literature has recognized a basis for a firm's competitive advantage with the effective configuration of resources (Ayabakan et al., 2017). When a firm has well-aligned access to resources, the execution of market responsiveness flows to the relevant place. The efficient mobilization of resources will enhance a firm's ability to cope with rising problems undoubtedly.

Analytical IT Capabilities in BA Value Chain Creation

IT capabilities have received enormous attention for its impact on firms as they play a pivotal role in data-driven processes related to data aggregation, analysis, and interpretation. Data aggregation focuses on data acquisition, transformation, and storage by combining heterogeneous data from multiple sources in a firm. Although concurrent technology has significantly improved data storage and processing speed, overcoming challenges in various data formats exist. Data analysis lays an emphasis on undertaking statistical reasonings to transform unorganized data into meaningful information and thus harvest stories in the data. Generally, three different types of analysis (i.e., descriptive, predictive, and prescriptive) are mentioned in the literature (Wang et al., 2018). In particular, text mining has become more significant as firms provide better customer services from unstructured data (Müller et al., 2016). Lastly, data interpretation is related to outputs generated by analytical tools. Data visualizations have been recognized as an essential tool, and interactive visual dashboards allow users to drill down for details and change analyses to examine factors that have a greater influence.

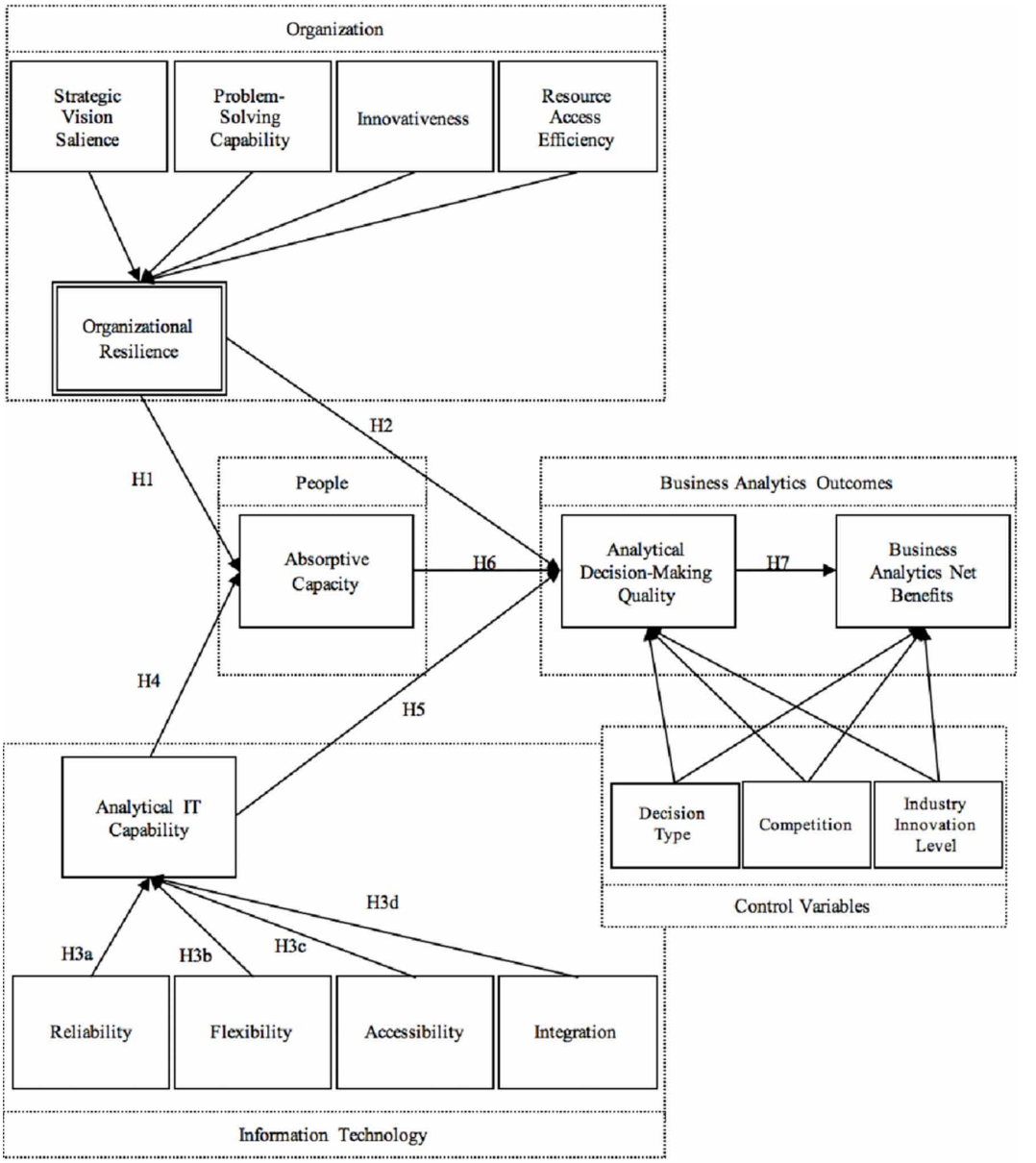
Absorptive Capacity in BA Value Chain Creation

IT capabilities have become standardized and homogenous, meaning that technology itself may not lead to competitive advantage (Chae et al., 2014), and that other capabilities should be bundled with technology for sustainable competitive advantage (Gupta & George, 2016). Big data investments have failed because of the insufficient absorptive capacity necessary to react to intelligence gleaned from data (Wang & Byrd, 2017). Absorptive capacity is a firm's ability to identify valuable knowledge, assimilate it into the firm's knowledge base, transform it, and apply it to innovation or competitive actions (Roberts et al., 2012). The concept is particularly important in enhancing the understanding of accessing, adjusting, and advancing the influence of BA under constant pressure to reorganize resources and refocus its knowledge base. As BA aims to correctly identify market situations, to transform situations into opportunities, and to sustain long-term competitive advantage, BA technology and absorptive capacity should go together to create a synergistic effect. Despite its significance and relevance, little attention has been paid to the impact of absorptive capacity on BA and organizational resilience. The literature has examined three different conceptualizations of absorptive capacity: asset, substantive capability, and dynamic capability (Roberts et al., 2012). The study follows the conceptualization of dynamic capability in the development of absorptive capacity.

HYPOTHESIS DEVELOPMENT

The theory of information value chain explains the transformation of data into decision-making as a synergistic combination among technology, people, and an organization (Abbasi et al., 2016). Figure 1 illustrates the research model that portrays the integrative nature of converting data into decision-making and firm performance in the BA value chain creation. Analytical IT capability manifests the technical aspect of the theory as enhanced analytical technology is critical to transforming data into useful information and actionable knowledge. Organizational resilience is the portion of the organizational context where BA is more effectively utilized and valued. Absorptive capacity is associated with the aspect of people in the theory that organizational members acquire data, interpret information, and report knowledge with emerging opportunities. Together with the theory of the information value chain, we posit that the congruence among technology, people, and organizational context converges on analytical decision-making quality and BA net benefits.

Figure 1. Value chain creation model in BA



A firm's absorptive capacity inherently resides in the mental models of organizational members, who are aware of the surrounding environment, bring information and knowledge to situations, and apply them for the purpose of performance enhancement (Iyengar et al., 2015; Wang & Byrd, 2017). In other words, absorptive capacity involves the coordination of interdependencies among various activities and the socialization of disparate knowledge from various people via collective interpretations of reality (Roberts et al., 2012). Dimensions of resilience such as strategic vision salience, problem-solving capability, innovativeness, and resource access efficiency are related to

the interplay of coordination and socialization among organizational members. Vision salience and problem-solving capability will empower organizational members to collect their capacity into one place to achieve goals, and innovativeness and resource access efficiency will help the firm not to be complacent and locate their resources for novel associations in the market. Thus, resilience serves as a governance mechanism to increase cooperation, collaboration, and communication in the organization and further to develop a collective mental model. Resilience will help generate a high level of shared values, a common language, and well-established norms (Nahapiet & Ghoshal, 1998). As organizational resilience will help improve absorptive capacity in a firm, we suggest the following hypothesis:

H1: Organizational resilience has a positive impact on absorptive capacity in the business analytics context.

How an organization achieves data-centric and evidence-based decision-making is a long-standing research question. Good decisions increase firm value while poor ones waste an organization's resources with ineffective capital investments and inefficient operations. Not only do quality decisions include right answers in fast-moving decision environments, but they engage critical parties in the analytical decision-making to attain smart alignment to action. Strategic vision salience guides firms to find the meanings of the impending challenges, to regroup themselves, and walk through implementations based on data. Leaders and members with vision salience see business reality in line with their strategic perspective and make data-driven decisions congruent to their goals (Carton et al., 2015). That is, they make sense of business situations by repositioning and reconfiguring their resources more effectively through the BA value chain creation. Problem-solving capability with feasible solutions is another facilitator for data-centric decisions. Creative problem-solving capability is known as leading to innovative, excellent decision-making (Althuizen & Reichel, 2016; Figl & Recker, 2016). Approaching problems outside of the box leads an organization to put together innovative ideas and reach landmark decisions in the BA value chain creation (Kock & Gemünden, 2016). A firm endeavoring to find evidence-based solutions to a problem needs support not only in terms of financial resources but also of technological and interorganizational resources in order to resolve pressing issues. As analytical decision-making quality is facilitated by organizational resilience, we provide the following hypothesis:

H2: Organizational resilience has a positive impact on analytical decision-making quality.

Big data are of no value without a suitable tool, and this burgeoning need demands firms to adopt cutting-edge analytical technology (Abbasi et al., 2016). System quality has long been regarded as an important part of IS success (DeLone & McLean, 2003). Some dimensions have general applicability, while the relative importance of each dimension is dependent upon a specific setting (Wixom & Todd, 2005; Xu et al., 2013). In the BA context, this study takes reliability, flexibility, accessibility, and integration as antecedents to analytical IT capabilities. Reliability refers to "the dependability of system operation" (Wixom & Todd, 2005). Flexibility refers to "the way the system adapts to changing demands of the user" (Wixom & Todd, 2005). Accessibility is described as the ease with which data can be accessed or extracted from the system (Wixom & Todd, 2005). The literature also defines integration as "the way the system allows data to be integrated from various sources" (Wixom & Todd, 2005). Strategic investments in analytical IT capabilities should accompany the establishment of quality systems that supports a firm's goals and objectives. Such supporting systems need to provide technological tools that are available, accessible, and sufficiently flexible to assist different types of analysis by integrating multiple sources of data from different databases. Thus, we present the following hypotheses in the context of BA:

H3a: Reliability is positively related to analytical IT capability.
H3b: Flexibility is positively related to analytical IT capability.
H3c: Accessibility is positively related to analytical IT capability.
H3d: Integration is positively related to analytical IT capability.

Analytical IT capabilities are useful in utilizing big data and deriving meaningful information from structured and unstructured data. Studies have also shown that the business value chain can be fostered by IT capabilities and absorptive capacity (Roberts et al., 2012). Absorptive capacity will increase when information flows throughout the organization. Quality data are useful, but discovering hidden patterns will enable the organization to achieve business insights and understand processes and outcomes. Past studies consistently support that modern IT plays a critical role in the development and maintenance of absorptive capacity (Roberts et al., 2012; Iyengar et al., 2015). Thus, we present the following hypothesis:

H4: Analytical IT capabilities have a positive impact on absorptive capacity in the business analytics context.

Firms face uncertain circumstances where the demand of data and analytics changes frequently (Kowalczyk & Buxmann, 2015), and such situations require firms to be equipped with a high level of flexibility and adaptability with regard to analytical capabilities. Various BA tools can help organizational members understand changing markets and make data-driven decisions by analyzing data in a timely and reliable manner. For instance, the massive reduction in the time and effort to integrate and analyze big data allows decision makers to search for information quickly and examine the pattern of the market efficiently. Research shows that the availability of analytical tools suitable for investigating the potential impact of actions gives members insights into situations and solutions of problems, which leads to effective decisions (Seddon et al., 2017). As effective BA improves data processing and data-centric decision support which in turn result in quality decision-making, this study tests the following hypothesis:

H5: Analytical IT capability has a positive impact on analytical decision-making quality.

Absorptive capacity is instrumental in elevating analytical decision-making quality. Knowledge gleaned from a firm's absorptive capacity offers a clearer perspective on the market landscape and the circumstances the firm faces. Valuable knowledge via a firm's absorptive capacity assists the reallocation and restructuring of resources and expands stakeholders' understanding of various issues at hand (Wang & Byrd, 2017). Disseminated knowledge empowers involved parties to make sense of market situations and put their capabilities into practice (Iyengar et al., 2015). Absorptive capacity is helpful in clearing away uncertainty, misperceptions, and confusion. It also forms the basis for transparency, reprioritization, and changes in decision-making by affording constant inflows of valuable knowledge to the firm (Kock & Gemünden, 2016). Thus, we present the following hypothesis:

H6: Absorptive capacity has a positive impact on analytical decision-making quality.

Net benefits are considered as a critical measure of IT acceptance and use, and such benefits include cost savings, expanded markets, incremental additional sales, reduced search costs, and time savings (DeLone & McLean, 2003). As studies use organizational benefits and business value interchangeably (Seddon et al., 2017), this study investigates value chain creation in BA and sets net benefits as the primary outcome. Although data are often regarded as agents of change, firms are yet to see this promise being fulfilled (NewVantage Partners, 2017). It implies that the abundance of data

and analytics tools do not necessarily mean that firms benefit from the information provided. When better decisions are made with the support from business analytics, organizational members sense the value of analytics and become satisfied with their endeavors to integrate BA into the fabric of the firm (Janssen et al., 2017). In the face of tough competition, high-quality decision-making relieves stakeholders of their worries and gives confidence to the parties involved in the decision-making. The benefits of BA emerge when it is proactively used across the corporate landscape and takes a central role in decision-making and implementation. Thus, we present the following hypothesis:

H7: Analytical decision-making quality has a positive impact on business analytics net benefits.

RESEARCH METHODS

The survey methodology was used to test our research model, and its measurement and structural models were examined by SmartPLS 2.0. All instruments used in this study, as shown in Appendix, were adapted from the existing literature on a seven-point Likert scale where 1 was "Strongly Disagree" and 7 was "Strongly Agree." Decision types, competition, and level of industry innovation were controlled to better examine the impact of value chain creation in BA. The survey questionnaire was administered to senior-level IT professionals representing companies that employ BA from various industries. To facilitate our data collection, we hired a leading online survey platform company which had a capability to reach out to sizable companies including Apple, IBM, SAP, or SAS in the field of BA. The use of the company increased our ability to cover the intended population of this study and thus enhanced the generalizability of the research results. Although we used the service of the company's market panels, the design of the survey, the appropriateness of responses, and the analysis of data were undertaken by the researchers. In particular, we included screen questions to obtain proper data: (1) What is your primary job responsibility? (2) How many years have you worked in the data analytics field? (3) How many years have you been working for your company? Also, an attention question to answer a specific one was included to check whether or not the respondent was actually reading the survey question. The data collection proceeded in two phases. A pilot study was first implemented, with a little over 50 responses who were selected from a larger pool of companies that use BA. Following a check on convergent and discriminant validity, items were changed and fine-tuned, and then the large-scale data collection launched. A total of 1,022 were invited to answer the survey, and 268 firms completed it, resulting in a 26.2% response rate. Respondents held job titles such as C-level executives, vice presidents, directors, senior business analysts, senior data scientists, and the like. Table 2 describes the demographic features of the sample studied in this research. Response/non-response bias was examined by comparing the earlier responses with the later ones. Both groups were compared with regard to annual sales and number of employees with a Chi-square test, and no significant differences were found.

Measurement Model

Convergent validity was tested by item loadings, composite reliabilities, and average variance extracted (AVE). All item loadings, shown in Table 3 in bold, were greater than .700, with the lowest composite reliability being .868. AVE in all constructs was greater than .500. Discriminant validity was examined by the square root of AVE for the associate construct which needs to be higher than all other correlations. As shown in Table 4, the data used in this study had no concern with discriminant validity.

A common method bias would be problematic in self-reported data, and this study followed the PLS model developed by Liang et al. (2007) to check the presence of this bias in the data. The average variances explained by substantive indicators and the method were .694 and .005, and the common method bias deemed to be not an issue.

Table 2. Demographic features of the sample studied

Characteristics	Percent	Characteristics	Percent
Annual Sales		**Industry**	
Less than 10 million	14%	Retail	5%
10 – 49.9 million	21%	Finance/Banking	9%
50 – 99.9 million	15%	Healthcare	6%
100 – 499.9 million	19%	Manufacturing	12%
500 – 1 billion	13%	Data Analytics	12%
Over 1 billion	9%	IT	20%
		Software/Telecommunication	8%
Number of Employees		Education	4%
100 – 249	16%	Government	4%
250 – 499	12%		
500 – 999	24%	**Job Position**	
1,000 – 2,499	16%	CEO/CIO/CTO	13%
2,500 and over	22%	Vice President/Director	17%
		Senior Data Analyst	4%
Gender		IT Manager	16%
Male	54%	Business Analysts	31%
Female	46%	Data Scientist/Software Engineer	10%
		Miscellaneous	10%

Table 3. Item loadings of confirmatory factor analysis

	AC	ACC	ADM	CAP	FLE	INN	INT	NB	PSC	RAE	REL	SVS
AC1	**0.729**	0.465	0.508	0.503	0.555	0.553	0.486	0.505	0.501	0.132	0.504	0.559
AC2	**0.784**	0.500	0.550	0.527	0.544	0.597	0.541	0.578	0.630	0.178	0.516	0.573
AC3	**0.772**	0.451	0.539	0.540	0.516	0.588	0.511	0.560	0.578	0.152	0.504	0.580
AC4	**0.776**	0.508	0.548	0.563	0.598	0.550	0.611	0.555	0.518	0.137	0.528	0.565
AC5	**0.805**	0.449	0.620	0.593	0.602	0.557	0.608	0.528	0.532	0.227	0.624	0.614
AC6	**0.798**	0.447	0.590	0.565	0.582	0.572	0.551	0.575	0.561	0.142	0.561	0.599
AC7	**0.786**	0.426	0.597	0.564	0.574	0.546	0.523	0.556	0.587	0.199	0.570	0.572
AC8	**0.771**	0.523	0.625	0.570	0.541	0.581	0.579	0.571	0.542	0.262	0.589	0.600
AC9	**0.785**	0.515	0.580	0.597	0.584	0.559	0.520	0.615	0.576	0.147	0.561	0.619
ACC1	0.581	**0.907**	0.575	0.529	0.586	0.565	0.474	0.564	0.493	0.095	0.651	0.543
ACC2	0.550	**0.941**	0.577	0.545	0.604	0.585	0.450	0.562	0.498	0.075	0.648	0.530
ACC3	0.562	**0.923**	0.559	0.582	0.606	0.602	0.450	0.579	0.506	0.077	0.603	0.552
ADM1	0.683	0.559	**0.892**	0.569	0.619	0.644	0.573	0.583	0.609	0.179	0.599	0.632
ADM2	0.633	0.516	**0.888**	0.524	0.573	0.569	0.552	0.540	0.604	0.177	0.586	0.592
ADM3	0.649	0.570	**0.888**	0.596	0.592	0.591	0.565	0.615	0.527	0.193	0.582	0.632
CAP1	0.542	0.431	0.478	**0.774**	0.493	0.420	0.457	0.481	0.323	0.093	0.480	0.507
CAP2	0.519	0.477	0.466	**0.761**	0.493	0.503	0.402	0.546	0.412	0.088	0.490	0.420
CAP3	0.471	0.472	0.449	**0.704**	0.442	0.503	0.400	0.473	0.441	0.072	0.353	0.403
CAP4	0.599	0.478	0.488	**0.824**	0.615	0.503	0.516	0.545	0.444	0.094	0.564	0.487
CAP5	0.645	0.481	0.577	**0.827**	0.611	0.489	0.555	0.572	0.470	0.114	0.573	0.506
FLE1	0.627	0.532	0.608	0.578	**0.879**	0.504	0.539	0.509	0.471	0.215	0.610	0.545
FLE2	0.674	0.525	0.607	0.615	**0.894**	0.579	0.564	0.581	0.512	0.175	0.593	0.582
FLE3	0.614	0.649	0.551	0.616	**0.863**	0.575	0.582	0.547	0.472	0.080	0.602	0.530
INN1	0.630	0.527	0.594	0.492	0.550	**0.838**	0.537	0.559	0.615	0.136	0.548	0.568
INN2	0.539	0.531	0.504	0.505	0.491	**0.791**	0.419	0.501	0.488	0.133	0.447	0.515
INN3	0.605	0.507	0.580	0.511	0.513	**0.851**	0.432	0.475	0.579	0.149	0.480	0.578
INN4	0.662	0.559	0.589	0.566	0.558	**0.874**	0.523	0.552	0.580	0.108	0.509	0.598
INT1	0.605	0.412	0.550	0.528	0.583	0.475	**0.888**	0.490	0.485	0.138	0.593	0.485
INT2	0.612	0.434	0.572	0.528	0.585	0.496	**0.868**	0.509	0.463	0.163	0.572	0.497
INT3	0.600	0.433	0.513	0.502	0.481	0.504	**0.825**	0.490	0.466	0.136	0.543	0.450
NB1	0.540	0.408	0.546	0.445	0.470	0.461	0.415	**0.769**	0.453	0.249	0.485	0.509
NB2	0.568	0.431	0.474	0.481	0.501	0.380	0.449	**0.759**	0.371	0.205	0.495	0.450
NB3	0.539	0.496	0.480	0.587	0.448	0.472	0.438	**0.790**	0.379	0.225	0.497	0.437
NB4	0.595	0.524	0.546	0.608	0.556	0.564	0.462	**0.810**	0.461	0.146	0.453	0.569
NB5	0.555	0.541	0.477	0.498	0.435	0.538	0.481	**0.755**	0.546	0.137	0.541	0.529
PSC1	0.667	0.486	0.576	0.482	0.505	0.589	0.494	0.525	**0.882**	0.161	0.514	0.507
PSC2	0.565	0.424	0.549	0.402	0.436	0.513	0.440	0.422	**0.848**	0.103	0.416	0.438
PSC3	0.586	0.461	0.532	0.476	0.461	0.612	0.456	0.493	**0.812**	0.085	0.496	0.527
RAE1	0.248	0.107	0.220	0.141	0.172	0.140	0.179	0.229	0.171	**0.865**	0.206	0.209
RAE2	0.178	0.086	0.127	0.089	0.153	0.245	0.113	0.189	0.091	**0.788**	0.147	0.156
RAE3	0.123	0.025	0.148	0.058	0.111	0.011	0.100	0.175	0.052	**0.753**	0.108	0.116
RAE4	0.124	0.025	0.147	0.062	0.098	0.005	0.131	0.185	0.091	**0.747**	0.136	0.126
REL1	0.653	0.583	0.626	0.564	0.603	0.555	0.643	0.578	0.521	0.209	**0.912**	0.587
REL2	0.650	0.605	0.584	0.555	0.614	0.499	0.565	0.557	0.485	0.162	**0.902**	0.580
REL3	0.622	0.667	0.588	0.609	0.639	0.551	0.589	0.584	0.521	0.165	**0.899**	0.559
VS1	0.730	0.517	0.619	0.563	0.600	0.596	0.547	0.613	0.535	0.235	0.603	**0.894**
VS2	0.642	0.492	0.633	0.491	0.509	0.579	0.453	0.564	0.508	0.191	0.480	**0.886**
VS3	0.634	0.554	0.603	0.540	0.565	0.622	0.477	0.536	0.503	0.109	0.610	**0.884**

Table 4. Descriptive statistics, correlation and average variance extracted

	AVE	CR	CA	Correlations											
				AC	ACC	ADM	CAP	FLE	INN	INT	NB	PSC	RAE	REL	SVS
AC	0.607	0.933	0.919	1											
ACC	0.853	0.946	0.914	.611***	1										
ADM	0.791	0.919	0.868	.737***	.617***	1									
CAP	0.607	0.885	0.838	.717***	.599***	.634***	1								
FLE	0.772	0.910	0.852	.727***	.648***	.669***	.687***	1							
INN	0.704	0.905	0.859	.728***	.633***	.677***	.618***	.630***	1						
INT	0.740	0.895	0.824	.704***	.495***	.634***	.604***	.640***	.571***	1					
NB	0.604	0.884	0.836	.720***	.615***	.652***	.673***	.622***	.622***	.577***	1				
PSC	0.719	0.885	0.804	.717***	.541***	.652***	.537***	.553***	.676***	.548***	.568***	1			
RAE	0.624	0.868	0.813	.226***	.089	.206***	.120	.177***	.157**	.170***	.249***	.138**	1		
REL	0.818	0.931	0.889	.709***	.685***	.662***	.638***	.685***	.592***	.662***	.634***	.563***	.197***	1	
SVS	0.789	0.918	0.866	.754***	.587***	.696***	.598***	.629***	.674***	.555***	.643***	.580***	.201***	.636***	1

CR: Composite Reliability, CA: Cronbach's Alpha
* Significant at $\alpha < .10$, ** Significant at $\alpha < .05$, *** Significant at $\alpha < .01$

Structural Model

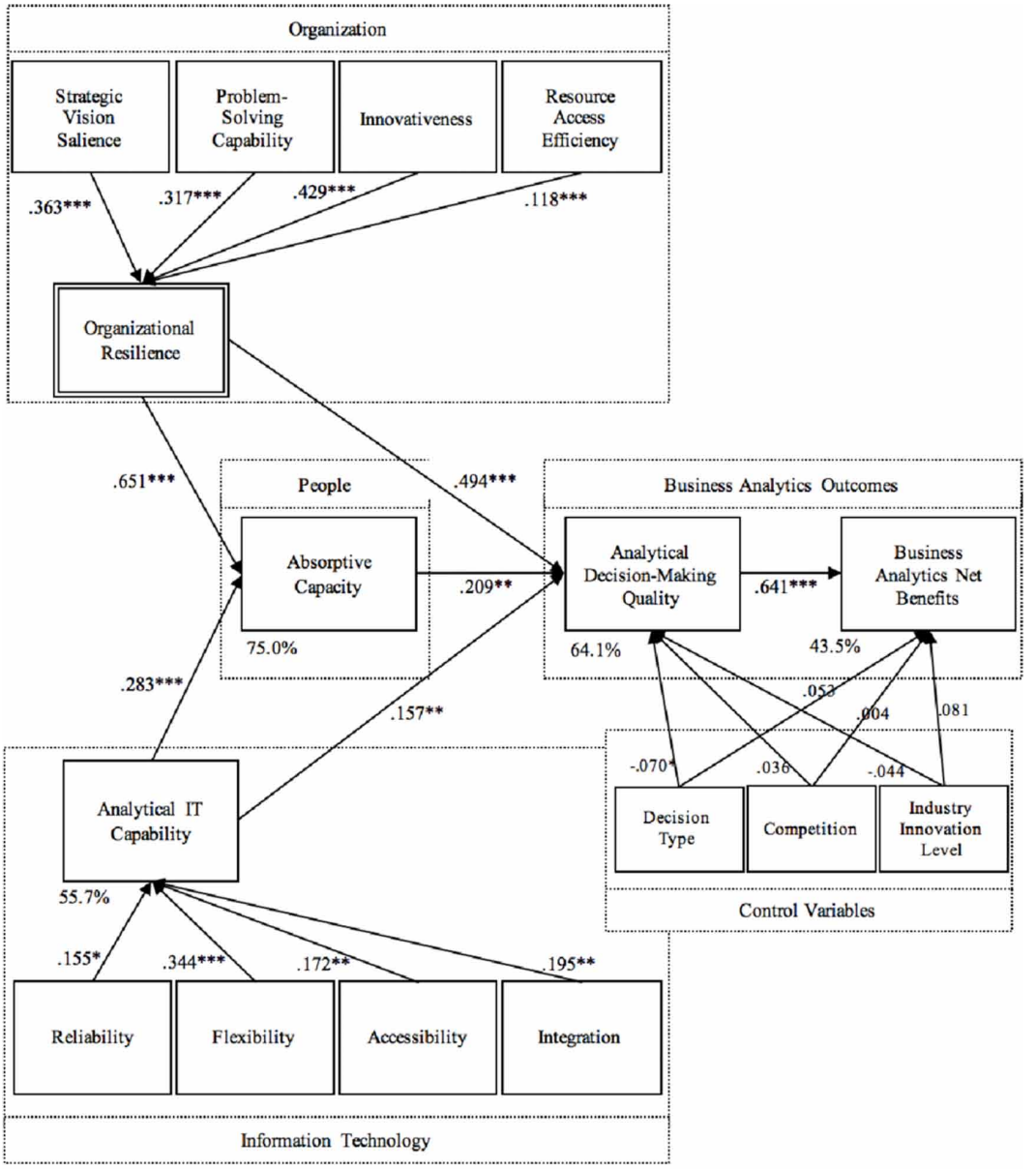
The BA value chain creation model was examined by reviewing path coefficients and the percentage of variance was determined, as shown in Figure 2. As hypothesized in H1 and H4, organizational resilience ($\beta = .651$, $p < 0.01$) and analytical IT capability ($\beta = .283$, $p < 0.01$) show significant influences on absorptive capacity. The results show that absorptive capacity is significantly impacted by organizational resilience more than by analytical IT capability. The capacity to absorb information and translate it into actionable knowledge does not depend solely on analytical IT capabilities but also on organizational resilience embedded in their strategic vision, problem-solving capability, innovativeness, and resource access efficiency. Subsequently, the research model examined the impact that organizational resilience, absorptive capacity, and IT capability bring to analytical decision-making quality. The structural model revealed their strong effects: organizational resilience ($\beta = .494$, $p < 0.01$), absorptive capacity ($\beta = .209$, $p < 0.05$), and analytical IT capability ($\beta = .157$, $p < 0.05$). The three constructs all increased analytical decision-making quality, and notably organizational resilience exhibited the strongest effect. As such, the results support H2, H5, and H6. With respect to antecedents to analytical IT capabilities, flexibility ($\beta = .344$, $p < 0.01$), accessibility ($\beta = .172$, $p < 0.05$), and integration ($\beta = .195$, $p < 0.05$) had a significant positive influence, supporting H3b, H3c, and H3d. Reliability showed a positive influence on analytical IT capability ($\beta = .155$, $p < 0.10$), but its significance is weak. It is an interesting result that flexibility, not reliability, emerges as the strongest factor for analytical IT capability. Last, but not least, analytical decision-making quality considerably enhanced BA net benefit ($\beta = .641$, $p < 0.01$) and thereby confirmed H7. Decision-making quality is shown to have a large impact on BA net benefits. As for control variables, decision type, competition, and industry innovation level were all insignificant apart from the link between decision type and analytical decision-making quality.

The variance in analytical IT capability is 55.7%. In the case of the variances in absorptive capacity and analytical decision-making quality, figures were 75.0% and 64.1%, respectively. In addition, the variance in business analytics net benefit is 43.5%.

DISCUSSION

A great interest in BA along with its variants such as big data analytics and business intelligence & analytics has been raised (Seddon et al., 2017). This study attempts to develop a research model that captures the BA value chain creation and examines relationships among organizational resilience, analytical IT capabilities, and absorptive capacity, and their impacts on decision-making quality. BA

Figure 2. Structural model results



* Significant at α < .10 ** Significant at α < .05 *** Significant α < .01

efficiency is a complex concept with multidimensional variables, and this study helps to reveal the business factors that are necessary for the successful deployment of BA in an organization.

Implications For Research

The theory of the information value chain argues that the aligned interaction among people, technology, and organizational context will convert data into information and further lead to knowledge and action

(Abbasi et al., 2016). Research has shown that investments in IT can enhance its value when combined with managerial skills, IT infrastructures, and a firm's intellectual capital (Gupta & George, 2016). In other words, the value chain creation in BA can be disappointing without the complementary support of human components and organizational contexts in incorporating valuable knowledge and insights into decision-making. This study presents a research framework that the interplay among analytical IT capabilities, organizational resilience, and absorptive capacity leads firms into BA effectiveness. This conceptualization and subsequent empirical confirmation provide findings that absorptive capacity and organizational resilience need to come together in order to realize IT investments into high quality decision-making for BA net benefits.

The first theoretical contribution of the study is explicating the vital role that organizational resilience plays in translating BA capabilities into insights and performance, which answers the first research question. When an organization functions with a flexible mindset and readiness to utilize technical benefits, it can realize and materialize the full potential of BA in the form of decision-making and tangible benefits (Raguseo et al., 2018). Organizational resilience is the ability to go through adversity and still rise out of difficulties refreshed and transformed. As the market becomes more turbulent and disrupted, organizational resilience has become an important trait not only in helping to maintain the competitive advantage of a firm but also in helping to renew and sharpen the firm in the constantly changing market. This study finds that organizational resilience increases the ability to absorb information and transform it into knowledge for effective decisions. This study also expands the BA literature by investigating the nature of organizational resilience, its role, and its impact on BA outcomes. BA can be successfully implemented when an organization is coupled with organizational resilience.

The second theoretical implication arises from answering the second research question that explicates the role of absorptive capacity in the BA value chain creation. The research model with an empirical test clarifies the antecedents to analytical decision-making quality. This research posits, besides analytical IT capabilities and organizational resilience, absorptive capacity as an important link between investments in BA and their outcomes. As previous studies have indicated (Gupta & George, 2016), BA has to be equipped with appreciating findings and reflecting them in decision-making. This organizational mechanism is characterized as an ability to identify significant information, assimilate it into a firm's routines, transform it into a firm's knowledge bases, and apply it to innovative decisions. Absorptive capacity has been treated as an important organizational capability in the IS research stream (Iyengar et al., 2015; Roberts et al., 2012), but to our knowledge, there is a dearth of studies delving into this important area in the BA context. In view of the theory of the information value chain, absorptive capacity highlights the element of people who actively engage in learning and applying knowledge to actions in a responsive manner.

Finally, this research, responding to the third research question of desired BA outcomes, adds insights to the extant literature by untangling the critical outcomes in the BA value chain creation. Without tangible goals and outcomes, analytics may struggle to find its role and position in an organization, but effective BA demonstrates its prowess in its results. The BA outcomes can take such forms as cost savings, expanded markets, incremental additional sales, reduction in the search effort, and time savings. Also, its value should be tangible in the organization, especially through an improved quality of decision-making and subsequent bottom line improvements. Together with its examination of the BA value chain creation, this research points to the vibrant outcomes. As discussed above, some firms do not reap benefits from big data capabilities, while others find financial improvements from BA investments (NewVantage Partners, 2017). A possible explanation of these conflicting findings is that a firm should have a proper alignment among organizational context, people, and analytical IT tools. A missing component in a firm's BA dynamics may bring unexpected or partial outcomes. Although firms recognize BA as a necessity, it does not mean that they reap the full benefits from it. In other words, firms need to have a proper BA technology with the organization's ability to interpret

data insightfully and a suitable organizational climate. When the three aspects are well aligned, firms may see synergistic effects in terms of the use of BA and the benefits received.

Implications For Practice

The most outstanding implication of practice is the significance of the organizational elements in transforming data into analytical decision-making. As the technique of sophisticated analytics via enormous computational capacity proliferates, organizations are pressured to equip themselves with the novel technology for the BA environment. This study, however, reports that organizational aspects, embodied as organizational resilience in this study, are more critical than IT capabilities as part of enhancing analytical decision-making quality for BA net benefits. In other words, firms need to pay close attention to organizational resilience along with technical advancement. It may be easy for firms to perceive the urgency of adopting cutting-edge analytical infrastructure, but it is essential for firms to examine whether or not they work on cultivating a necessary organizational climate for the BA effectiveness. Firms with a high level of strategic vision salience, problem-solving capability, innovativeness, and resource access efficiency in the BA value chain creation arrive at quality decisions much more effectively than those with a low level of organizational resilience. The organizational climate help firms resurface from challenges and lead them to stay stronger during times of uncertainties.

The second implication for practice is derived from findings that the direct impact of analytical IT capability on analytical decision-making quality is less than that of absorptive capacity. These results are associated with the explanation that firms may not expect an immediate benefit from BA technology alone. Preferably, firms should extend their ability to identify valuable knowledge, assimilate it into their decision-making loop, and transform it into effective actions. This absorptive capacity is a critical factor for quality decision-making and further BA net benefits. That is, firms need to examine absorptive capacity as a crucial measure for understanding their BA effectiveness.

Combining these implications together, this study encourages not to lose sight of the elements of organizational context and people in the BA value chain creation. A firm's investments in IT must accompany an increasing resilient climate and absorptive capacity in order to expand the BA performance as they go through interpreting data and leading them to insights to actions, which in turn escalates the performance of BA.

Limitations and Suggestions For Future Research

This study has some limitations which may open new opportunities for future studies. The study has proposed and tested the BA value chain model, but applying and interpreting the model in a new context will require modifications. As this study used a cross-sectional survey, it relied on the perception of the respondents. Respondents may have a tendency to rate their perceptions in a positive way. This calls for more studies and experiments to verify and confirm the results of the present study in different settings. This study has used a single respondent from each firm to measure constructs at the organizational level, and future studies may attempt to use multiple respondents in varying contexts.

CONCLUSION

Firms are required to reconfigure their resources flexibly, based upon changing market conditions. In particular, firms have turned the spotlight on BA, which helps them recognize the surrounding circumstances and strive to transform both opportunities and threats into moments for improvement, renewal, and innovation. This study develops value chain creation in BA by encompassing data, IT, organization, and people and the influence on all of these on BA performance. This study reveals the criticality of organizational resilience and absorptive capacity in enhancing the quality of decision-making in addition to analytical IT capability. In creating values through investments in BA, firms should consider reinvigorating the soft dimensions of vision, drive for innovation, and the capacity to embrace knowledge and translate all these into decisions.

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APPENDIX

Table 5. Measurement items for the constructs

	AVE	CR	CA	Correlations											
				AC	ACC	ADM	CAP	FLE	INN	INT	NB	PSC	RAE	REL	SVS
AC	0.607	0.933	0.919	1											
ACC	0.853	0.946	0.914	.611***	1										
ADM	0.791	0.919	0.868	.737***	.617***	1									
CAP	0.607	0.885	0.838	.717***	.599***	.634***	1								
FLE	0.772	0.910	0.852	.727***	.648***	.669***	.687***	1							
INN	0.704	0.905	0.859	.728***	.633***	.677***	.618***	.630***	1						
INT	0.740	0.895	0.824	.704***	.495***	.634***	.604***	.640***	.571***	1					
NB	0.604	0.884	0.836	.720***	.615***	.652***	.673***	.622***	.622***	.577***	1				
PSC	0.719	0.885	0.804	.717***	.541***	.652***	.537***	.553***	.676***	.548***	.568***	1			
RAE	0.624	0.868	0.813	.226***	.089	.206***	.120	.177***	.157**	.170***	.249***	.138**	1		
REL	0.818	0.931	0.889	.709***	.685***	.662***	.638***	.685***	.592***	.662***	.634***	.563***	.197***	1	
SVS	0.789	0.918	0.866	.754***	.587***	.696***	.598***	.629***	.674***	.555***	.643***	.580***	.201***	.636***	1

CR: Composite Reliability, CA: Cronbach's Alpha
* Significant at α < .10, ** Significant at α < .05, *** Significant at α < .01

Dong Kyoon Yoo is an Associate Professor of the Department of Computer Information Systems at Virginia State University. He earned a Ph.D. from the University of Toledo. His articles have appeared in Journal of Knowledge Management, Journal of Computer Information Systems, Journal of Information and Knowledge Management, International Journal of Quality & Reliability Management and International Journal of Services and Operations Management. He has presented articles on business analytics, knowledge management, virtual teams, ERP systems, and project management in conferences. His research interests are business analytics, platform ecosystems, knowledge management, and technology acceptance.

James Jungbae Roh is Associate Professor of Operations Management at Rowan University, USA. Dr. Roh received his Ph.D. in Manufacturing Management, MBA in management information systems and MA in Economics from the University of Toledo, and BA from Dongguk University, Seoul, Korea. His research interests center on the interface of supply chain strategy, sustainability, and technology management. His articles have appeared in Business Horizons, Information & Management, International Journal of Production Economics, International Journal of Production Research, Journal of Supply Chain Management, and Production Planning & Control, among others.