2017-01-01

Big data analytics and firm performance: Effects of dynamic capabilities

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http://hdl.handle.net/10026.1/5544

10.1016/j.jbusres.2016.08.009
Journal of Business Research
Elsevier BV

THE IMPACT OF BIG DATA ANALYTICS ON FIRM PERFORMANCE: THE MEDIATING EFFECT OF PROCESS-ORIENTED DYNAMIC CAPABILITIES

Abstract

Drawing on the resource-based view and the literature on big data analytics (BDA), information system (IS) success and the business value of information technology (IT), this study proposes a big data analytics capability (BDAC) model. The study extends the above research streams by examining the direct effects of BDAC on firm performance (FPER), as well as the mediating effects of process-oriented dynamic capabilities (PODC) on the relationship between BDAC and FPER. To test our proposed research model, we used an online survey to collect data from 297 Chinese IT managers and business analysts with big data and business analytic experience. The findings confirm the value of the entanglement conceptualization of the hierarchical BDAC model, which has both direct and indirect impacts on FPER. The results also confirm the strong mediating role of PODC in improving insights and enhancing FPER. Finally, implications for practice and research are discussed.

Keywords: Big Data Analytics, Big Data Analytics Capability, Business Values, Process-oriented Dynamic Capabilities, Firm Performance.

1 INTRODUCTION

Big data analytics (BDA) is emerging as a *hot* topic among scholars and practitioners. BDA is defined as a holistic approach to managing, processing and analyzing the *5 Vs*' data-related dimensions (i.e., volume, variety, velocity, veracity and value) in order to create actionable ideas for delivering sustained value, measuring performance and establishing competitive advantages (Fosso Wamba et al., 2015). Some practitioners and scholars have gone so far as to suggest that BDA is the "fourth paradigm of science" (Strawn, 2012, p.34), a "new paradigm of knowledge assets" (Hagstrom, 2012, p. 2), or "the next frontier for innovation, competition, and productivity" (Manyika et al., 2011, p.1). All these assertions are primarily driven by the ubiquitous adoption and use of BDA-enabled tools, technologies and infrastructure including social media, mobile devices, automatic identification technologies enabling the internet of things, and cloud-enabled platforms for firms' operations to achieve and sustain competitive advantage. For example, BDA allows for improved data-driven decision making and innovative ways to organize, learn and innovate (Kiron, 2013, Yiu, 2012); thus, it reinforces customer relationship management, improves the management of operations risk, and enhances operational efficiency and overall firm performance (Kiron, 2013).

Yet prior studies of the business value derived from information systems (IS) investments have reported mixed results, resulting in the so-called 'IT productive paradox'. Indeed, some scholars have argued that IS investments do not necessarily lead to improved operational efficiency and effectiveness (Solow, 1987, Strassmann, 1990, Roach et al., 1987), while others identified a positive association between IS investments and firm performance (Brynjolfsson and Yang, 1996, Barua et al., 2004, Barua et al., 1995). Their findings suggest that the absence of a positive link between IS investment and firm performance found by prior studies may be explained by several factors including the unavailability of appropriate data, the existence of time lags between IS investments and the business value generated from these investments, the absence of an assessment of the indirect benefits of IT, and the level of analysis of IS-related benefits (Brynjolfsson and Hitt, 2000, Devaraj and Kohli, 2003, Brynjolfsson and Yang, 1996, Anand et al., 2013). In fact, within this stream of research, eminent scholars argue that the impact of IT on firm performance may be mediated by a number of intermediate variables (Mooney et al., 1996, Anand et al., 2013). Furthermore, they propose applying a broader view of IT resources by integrating a multidimensional perspective into studies of the business value of IT or IT capabilities (Bharadwaj, 2000, Bhatt and Grover, 2005, Santhanam and Hartono, 2003). In this paper, we extend this stream of research by examining factors that contribute to improved firm performance as a result of BDA investments. More specifically, the study aims to examine the following research questions:

i. How BDA capabilities are measured and their overall uses are linked with firm performance?

ii. Do process-oriented dynamic capabilities (PODC) play a mediating role in the relationship between BDAC and FPER?

To address these research questions, this research draws on the emerging literature on BDA, IT capabilities as well as the resource-based view (RBV). The remainder of this paper is structured as follows: First, definitions of big data analytics are provided. This is followed by the presentation of selected studies on IT capabilities and big data analytics capabilities. Then, the research model and our research hypotheses are presented, followed by the research design. The subsequent sections present the data analysis and findings of the study, the discussion, and the conclusion and implications for research and practice.

2 BIG DATA ANALYTICS AS A NEW ENABLER OF COMPETITIVE ADVANTAGE

BDA is now considered as a game changer enabling improved business efficiency and effectiveness because of its high operational and strategic potential. The emerging literature on BDA has identified a positive relationship between the deployment of customer analytics and firm performance (Germann et al., 2014). For example, BDA allow firms to analyze and manage strategy through a data lens (Brands, 2014). Indeed, BDA is increasingly becoming a crucial component of decisions-making processes in businesses (Hagel, 2015). So it is not surprising that BDA is now considered as "a major differentiator between high-performing and low-performing organizations," as it allows firms become proactive and forward-looking, decreases customer acquisition costs by about 47% and enhances firm revenue by about 8% (Liu, 2014). The literature highlights the example of Target Corporation, which uses BDA through its loyalty card program to track customers' purchasing behaviors and predict their future buying trends. Amazon.com is another example of firm that is capitalizing on BDA. Indeed, almost 35% of purchases made on Amazon.com are generated from personalized purchase recommendations to customers based on BDA (Wills, 2014). Another example discussed in the literature is GE, which is planning to use BDA to improve the efficiency of the 1,500 gas turbines it monitors by means of software and network optimization, as well as to improve the dispatching of service and the coordination of gas and power systems. If realized, these benefits could lead to $66 billion in fuel savings over the next 15 years (Ward, 2014).

BDA is expected to have tremendous impacts within a variety of industries (Chen and Zhang, 2014). For example, major retailing firms are presently leveraging big data capabilities to improve the customer experience, reduce fraud, and make just-in-time recommendations (Tweney, 2013). In the healthcare sector, BDA is expected to reduce operational costs and improve the quality of life (Liu, 2014). In manufacturing and operations management, BDA is considered to be an enabler of asset and business process monitoring (Davenport et al., 2012b), supply chain visibility, enhanced manufacturing and industrial automation (Wilkins, 2013), and improved business transformation (Gardner, 2013).

3 IT CAPABILITIES AND BIG DATA ANALYTICS CAPABILITIES

Eminent scholars argue that it is important to take broader view of IT to better capture the business value of IS investments and deal with the IT 'productive paradox' (Bharadwaj, 2000, Bhatt and Grover, 2005, Santhanam and Hartono, 2003). They suggest focusing on IT capability, which is defined as the "firm's ability to mobilize and deploy IT-based resources in combination or co-present with other resources and capabilities" (p. 171) (Bharadwaj, 2000). Studies on IT capability have commonly used the RBV (Bharadwaj, 2000, Santhanam and Hartono, 2003), which originated from strategic management (Ryu and Lee, 2013, Zee and Jong, 1999). In this stream of research, studies argue that competitive advantage is achieved by deploying and using distinctive, valuable, and inimitable resources and capabilities (Bhatt and Grover, 2005). In fact, the concept of IT capability is based on the assumption that, while resources can easily be replicated, a distinctive set of capabilities mobilized by a firm is not easy to replicate and will lead to sustained competitive advantages (Santhanam and Hartono, 2003). Strategic management scholars argue that "investments into different IT assets are guided by firms' strategies and deliver value along performance dimensions consistent with their strategic purpose" (p. 763) (Aral and Weill, 2007). For this stream of research, IT capability will be used to achieve strategic integration by applying the capability for IT functionality to both shape and support business strategy (Zee and Jong, 1999). Moreover, any original capability will always lead to sustained competitive advantage through its path dependency, causal ambiguity, and social complexity (Porter and Millar, 1985). Consistent with prior studies (Davenport, 2006, Davenport and Harris, 2007, Goes, 2014, McAfee and Brynjolfsson, 2012b), we view BDAC as an important organizational capability leading to sustainable competitive advantage in the big data environment. The study also argues that original capability will always lead to sustained competitive advantage through its path dependency, causal ambiguity, and social complexity (Porter and Millar, 1985). Consistent with several earlier studies (Davenport, 2006, Davenport and Harris, 2007, Goes, 2014, McAfee and Brynjolfsson, 2012b), in this study, we view BDAC as an important organizational capability leading to sustainable competitive advantage in the big data environment.

Many typologies of IT capabilities have been proposed. For example, Bhatt and Grover (2005) characterized IT capability through value, heterogeneity, and imperfect mobility. They argued that IT capability value and heterogeneity are "necessary conditions for competitive advantage," (p. 258) while imperfect mobility is "necessary for sustained advantage" (p. 258) (Bhatt and Grover, 2005). They further conceptualized three different types of capabilities: value capability (e.g., quality of IT infrastructure), competitive capability (e.g., quality of IT business expertise), and dynamic capability (e.g., intensity of organizational learning) in order to better understand the sources of IT-based competitive advantage. Using a sociomaterialistic perspective in conceptualizing a firm's IT capability, Kim et al. (2012) considered IT capability to be a function of IT management capability, IT personnel capability and IT infrastructure capability. They argued that sociomaterialism-based modeling underscores complementarities among the three IT capabilities identified, as opposed to the dominant traditional approaches in IS, in which IT capability was characterized in terms of "unidirectional and unrelated conceptualization" (p. 329). The authors also tested and found a positive relationship between IT capability and firm performance (business process and financial). This result is consistent with prior studies that assessed the relationship between IT capability and related outcomes (e.g., firm performance, firm agility, stock market returns) (Lin, 2007, Gibb et al., 2011).

In a similar spirit with IT capabilities literature, we conducted a review on big data analytics capabilities which presents us three predominant dimensions, that is, management, infrastructure and personnel capabilities. For instance, McAfee and Brynjolfsson (2012b) put forward personnel management, technology infrastructure, and corporate decision making as critical capabilities across organizations in data economy. Similarly, Kiron et al. (2014) identify organization culture, analytics platform, and employees' analytics skills as core dimensions of BDA . Furthermore, Davenport et al. (2012a) highlights that management, people and technology dimensions are interlinked in big data environment, which help each other to enhance broader firm performance . These dimensions of BDA and their relationships are supported by Barton and Court (2012) who illuminate that management capability is important to optimize decision models, technology capability is essential to explore and manage variety of data and finally, data science capability is important to understand, develop and apply analytics models.

4 RESEARCH MODEL AND RESEARCH HYPOTHESES

Drawing on the emerging literature on BDA capabilities and IT capabilities, this study proposes the research model shown in Figure 1 using RBV and sociomaterialism theory. Contrary to the extant literature on IT capabilities (e.g., Kim et al., 2011), this study proposes BDA capabilities as a third-order, hierarchical model manifested in three second-order constructs – BDA infrastructure capability, management capability, and personnel capability – and eleven first-order constructs: BDA planning, investment, coordination, control, connectivity, compatibility, modularity, technical knowledge, technology management knowledge, business knowledge and relational knowledge (see Figure 1). The study also argues that BDA capabilities have a significant impact on PODC, which in turn influences FPER.

Drawing on the RBV (Grant, 1991), relational sociomaterialism (Orlikowski and Scott, 2008, Orlikowski, 2007, Kim et al., 2012), process-oriented dynamic capabilities, and the emerging literature on BDA (Barton and Court, 2012, McAfee and Brynjolfsson, 2012a, Davenport and Harris, 2007, Davenport et al., 2012a, Kiron et al., 2014), this study proposes an ‘entanglement’ view of BDAC that has multiple complementary dimensions that synergistically allow unique firm performance to be achieved (Clemons and Row, 1991, Powell and Dent-Micallef, 1997, Tippins and Sohi, 2003, Kim et al., 2012) (Figure 1). Similar to (Kim et al., 2012), we argue that BDA infrastructure capability, personnel capability and management capability are the key components of a firm’s BDAC (see Table 1).

Prior studies have identified a positive link between IT capability and firm outcomes. For example, (Lu and Ramamurthy, 2011, p. 931), using a matched-pair field survey of business and information systems executives in 128 organizations, identified a significant positive relationship between IT capability and two types of organizational agility: market capitalizing agility and operational adjustment agility. Similarly, on the basis of matched survey data collected from 214 Chinese IT and business executives from manufacturing firms, (Chen et al., 2014) found that IT capability has a positive effect on firm performance. They also found that dynamic capability of the business process mediates the relationship between IT capability and firm performance. Using a cross-sectional sample of 155 banking firms, (Lin, 2007, p. 93) showed that IT capability and human capital investment “contribute directly to the overall value-creation performance of banking firms”. (Kim et al., 2012) applied a relational sociomaterialistic conceptualization of IT capability and found a positive and significant relationship between IT capability and a firm’s performance. Based on this observation, our study suggests testing not only the direct effects of BDAC on FPER but also the mediating effects of PODC on the relationship between BDAC and FPER (Figure 1).

Therefore, we put forward the following hypotheses:

H1: BDAC has a significant positive effect on PODC.

H2: BDAC has a significant positive effect on FPER.

H3: BDAC has a significant positive indirect effect on FPER, which is mediated by a positive effect on PODC.

Table 1. Constructs and definitions

Construct and Definition	Source
Big data analytics capability (BDAC) is broadly defined as the competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force.	Adapted from (Kiron et al., 2014).
BDA infrastructure capability refers to the ability of the BDA infrastructure (e.g., applications, hardware, data, and networks) to enable the BDA staff to quickly develop, deploy, and support necessary system components for a firm.	Adapted from (Kim et al., 2012) p. 335)
Big data management capability refers to the BDA unit's ability to handle routines in a structured (rather than ad hoc) manner to manage IT resources in accordance with business needs and priorities.	Adapted from (Kim et al., 2012) p. 336)
Big data analytics personnel capability refers to the BDA staff's professional ability (e.g., skills or knowledge) to undertake assigned tasks.	Adapted from (Kim et al., 2012) p. 336)
PODC refers to the extent to which a firm can develop or acquire required competences to change its existing business processes in a more robust way than its competitors in terms of coordination, integration, cost reduction, and business intelligence and learning related to BDA projects.	Adapted from (Kim et al., 2011)
FPER refers to the firm's ability to gain and retain customers, and to improve sales, profitability, and return on investment (ROI).	(Tippins and Sohi, 2003, Mithas et al., 2011)

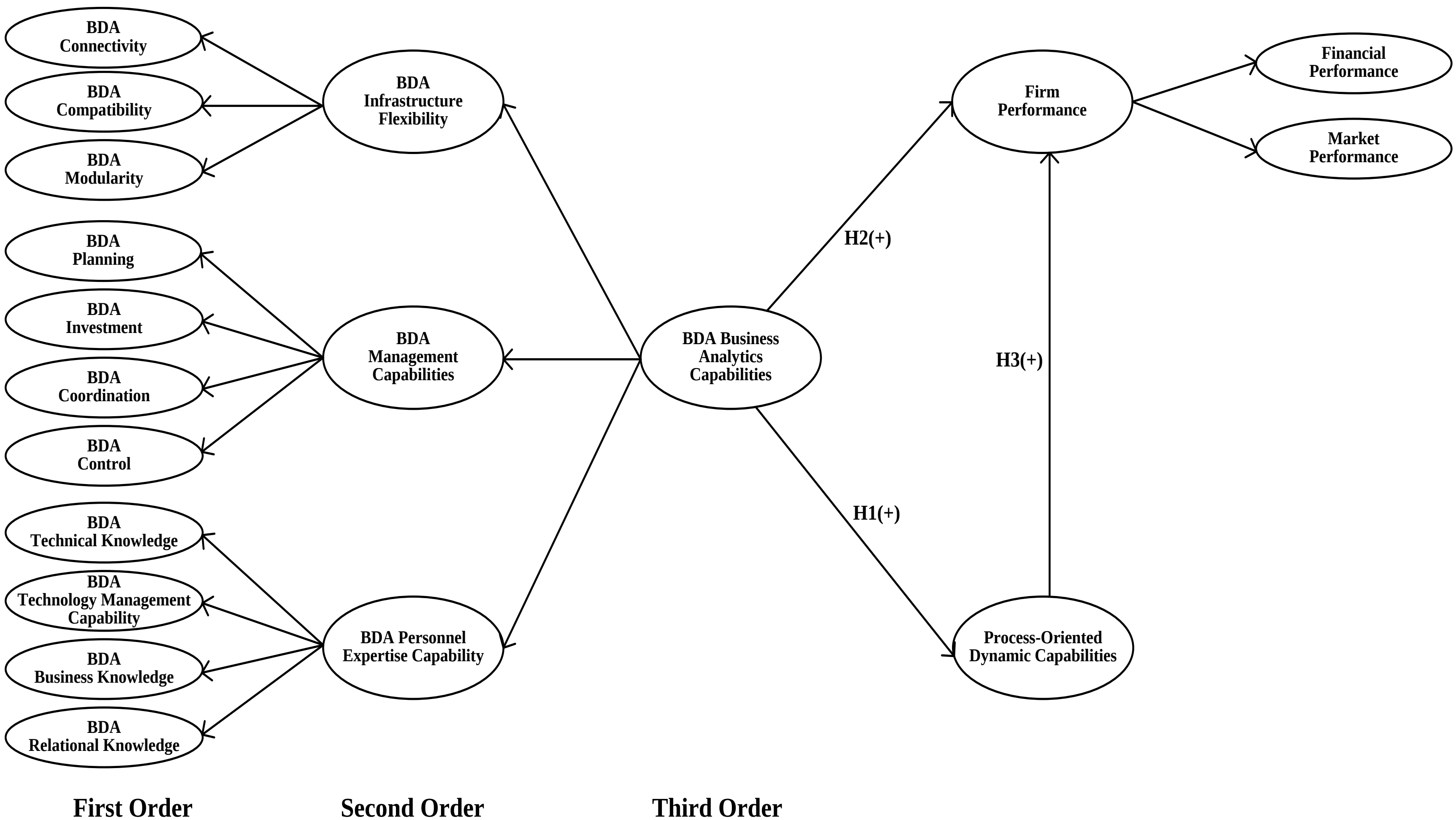

Figure 1. Research model

5 RESEARCH METHOD

The study is based on positivist research approach assuming that world of phenomena has an objective reality which can be expressed in causal relationships and measured in data (Straub et al., 2004). Using the positivist approach, the study captured the objective and social reality by survey measures to identify the BDA capabilities in order to address the research questions. As part of this approach, we initially explored literature to identify the dimensions of BDA capabilities, their overall impact on firm performance and the mediating role PODC between BDAC and FPER. Based on RBV and sociomaterialism theory, we conceptualized the research model, developed the survey and validated the hypothesized relationships using partial least squares (PLS) based structural equation modelling (SEM).

5.1 Survey, Scaling and Sampling

This study adopted the questionnaire based survey method because it captures causal relationships between constructs and hence provides generalizable statements on the research setting (Pinsonneault and Kraemer, 1993). Moreover, surveys can accurately document the norm, identify extreme information and delineate associations between variables in a sample (Gable, 1994). Straub et al. (2004) also recommended survey research for explanatory and predictive theory in order to ensure greater confidence in the generalizability of the results.

The survey questionnaire used in the study consists of previously published multi-item scales with favorable psychometric properties (see Table 3). All the constructs in the model were measured using 7-point Likert scales (e.g., strongly disagree–strongly agree). A cross-sectional survey was used to collect the data and test the research model. The data collection consisted of three steps. Before the main survey, a pilot study was conducted to ensure that the measures were valid and reliable. The questionnaires were distributed to on-the-job postgraduate students in the Master of Engineering program in one of the leading Chinese universities. Among them only those who have big data and business analytics experiences are invited to fill in the questionnaire. 42 usable questionnaires were collected and the measures ensured good reliability and validity. The final items used in the questionnaire and their sources are listed in Table 3.

We collected data from China because it is one of the most active areas in e-commerce and m-commerce development and the online retail markets of China account around 60% percent in Asia (Harca 2015). It's a hugely significant retail market that attracted scholars and practitioners because of the wealth of data gathered. Chinese practitioners have the opportunities to pinning it down and making the data useful, however these practices are not limited to China alone, it can be used to other countries. We designed to study the general capabilities that these practitioners need to have in big data analytics and avoid to choose culture-sensitive concepts, thus we believe our data has its generalisability to other countries.

The main survey was conducted by a market research firm with a database of more than 10,000 Chinese IT managers and business analysts. There are two reasons why we choose this market firm: 1) it has the resource of a large list of more than 10000 Chinese IT managers and business analytic, 2) it has a professional fame for its survey quality control. An online questionnaire was distributed to 500 people using simple random sampling. In around two weeks, we received responses from 315 people. Due to the online nature of the data collection, the study did not provide any missing value because respondents were not allowed to proceed to the next question if they do not answer a particular question. The study enabled this survey option because it helps respondents answer the question and move on without skipping any question. However, this option resulted into 20 incomplete answers and the study excluded those responses from the dataset. We also excluded those responses from the study that were provided by managers without any big data and business analytic experience. After these procedures, 225 questionnaires were usable. To collect more data, we asked the market research firm to distribute the survey to another 200 people, and 90 more responses were received. In the end, there were 297 usable questionnaires. Of the respondents, 77.7% were male, and the majority (more than 86%) had a college qualification or above. Table 2 represents the respondents' demographic characteristics and the characteristics of their firms.

Table 2. Demographic profile of respondents

Dimension	Category	Percentage (%)
Education	No formal qualification	0
	Primary school qualification	1.35
	Secondary school qualification	2.36
	College qualification (diploma/certificate)	9.46
	Undergraduate degree	67.57
	Postgraduate degree (Master/Ph.D.)	19.26
Age	18–25 years old	22.30
	26–33 years old	43.92
	34–41 years old	30.07
	42–49 years old	3.72
	50 years old or older	0
Gender	Male	77.70
	Female	22.30
Industry	Accommodation and food service activities	5.74
	Administrative and support service activities	6.76
	Agriculture, forestry and fishing	1.35
	Arts, entertainment and recreation	1.69
	Construction	4.73
	Education	2.36
	Electricity, gas, steam and air conditioning supply	1.01
	Financial and insurance activities	12.84
	Human health and social work activities	0
	Information and communication	36.15
	Manufacturing	14.19
	Mining and quarrying	0.68
	Professional, scientific and technical activities	3.04
	Public administration and defense; compulsory social security	0
	Real estate activities	1.69
	Transportation and storage	2.03
	Water supply; sewerage, waste management	0
	Wholesale and retail trade; repair of motor vehicles and motorcycles	2.03
	Other service activities	3.38

6 CONFIRMATORY FACTOR ANALYSIS USING PLS-SEM

In order to assess the higher-order BDA capabilities model, the study applied partial least squares based structural equation modeling (PLS-SEM) because it estimates hierarchical models by removing the uncertainty of inadmissible solutions using its flexible assumptions (Hair et al., 2011, Hulland et al., 2010). We applied PLS-SEM because it ensures greater theoretical parsimony and less model complexity to estimate the hierarchical model (Edwards, 2001, Wetzels et al., 2009). For instance, using PLS path modeling, (Wetzels et al., 2009) recently developed a fourth-order, hierarchical-reflective model of online experiential value to predict e-loyalty. Akter et al. (2013, 2010) developed a third-order service quality model and a second-order trustworthiness model using PLS-SEM. Hierarchical modeling can be done in two different ways depending on the relationship between latent variables and manifest variables: *hierarchical-reflective modeling* and *hierarchical-formative modeling*. In the reflective model, the latent variables affect the manifest variables ($LVs \rightarrow MVs$), whereas in the formative model, the manifest variables affect the latent variables ($MVs \rightarrow LVs$). The reflective construct is generally viewed as giving rise to its indicators (Fornell and Bookstein, 1982), but the formative construct views its indicators as defining characteristics. Based on the established guidelines on hierarchical modelling (Wetzels et al., 2009, Becker et al., 2012), the study applied PLS-SEM to estimate the third-order, reflective BDA capabilities model.

6.1 Measurement Model

In order to assess the hierarchical research model, we used PLS Graph 3.0 (Chin, 2001) to estimate the parameters in the outer and inner models. In this case, we applied PLS-SEM with a path weighting scheme for the inside approximation. Then we applied nonparametric bootstrapping (Efron and Tibshirani, 1993, Chin, 2010b) with 5,000 replications to obtain the standard errors of the estimates (Hair et al., 2013). The measurement model was evaluated prior to the structural model, in terms of construct reliability, unidimensionality, convergent validity, and discriminant validity. The BDA capability model is a third-order hierarchical model with 3 second-order constructs and 11 first-order constructs with a total of 50 items. In Table 3, some descriptive statistics on the constructs are presented. Convergent validity, unidimensionality and discriminant validity were further evaluated in the following sections.

Following Anderson and Gerbing (1988), we confirmed convergent validity as all the items were significantly loaded on their designated latent variables. A higher-order confirmatory factor analysis (CFA) (Bentler, 1989) was carried out to test the convergent validity of each construct. The standardized CFA loadings in Table 4 present evidence of convergent validity. All the item loadings were greater than the threshold of 0.70 (Fornell and Larcker, 1981a). We ensured unidimensionality of the measurement model using four criteria. First, unidimensionality was supported by higher internal consistency (i.e., loadings > 0.707, $p < 0.01$) of items under each construct (Chin, 2010a). Second, unidimensionality was established by Cronbach's alpha, which exceeds 0.70 for all the constructs (Nunnally and Bernstein, 1994). Third, the AVEs of each construct were greater than 0.50, which adequately reflect unidimensionality (Fornell and Larcker, 1981b). Because, higher AVEs explain that the observed items explain more variance than the error terms. Finally, unidimensionality was supported by the composite reliability of each construct, which exceeds 0.80 cut-off value (Segers, 1997, Hair et al., 2013). Composite reliability is the most robust measure of a construct's internal consistency because it prioritizes items as per their reliability in estimating measurement model (Hair et al., 2011). We also ensured discriminant validity by estimating the square root of the AVEs in the diagonals of the correlation matrix in Table 5. The findings show that the square root of AVE of a construct was higher than its correlations with other constructs, suggesting that the measurement model in this study has good discriminant validity. This test highlights that the latent constructs have different items and they are conceptually distinct from each other(Chin, 2010a).

Table 3. Construct and survey items

	Sub-dimensions	Mean	SD
BDA infrastructure flexibility (Kim et al., 2012)	**Connectivity (CN) (α =0.86; CR: 0.91; AVE: 0.71)**		
	Compared to rivals within our industry, our organization has the foremost available analytics systems. All other (e.g., remote, branch, and mobile) offices are connected to the central office for sharing analytics insights. Our organization utilizes open systems network mechanisms to boost analytics connectivity. There are no identifiable communications bottlenecks within our organization for sharing analytics insights.	5.09	1.16
	Compatibility (CP) (α =0.92; CR: 0.94; AVE: 0.80)	5.10	1.26
	Software applications can be easily used across multiple analytics platforms.		
	Our user interfaces provide transparent access to all platforms.		
	Information is shared seamlessly across our organization, regardless of the location.		
	Modularity (MOD) (α =0.88; CR: 0.92; AVE: 0.74)	5.172	1.152
	Reusable software modules are widely used in new system development.		
	End users utilize object-oriented tools to create their own applications		
	Analytics personnel utilize object-oriented technologies to minimize the development time for new applications.		
	The legacy system within our organization restricts the development of new applications.		
BDA management capabilities (Kim et al., 2012)	**Sub-dimensions**	**Mean**	**SD**
	Planning (PLAN) (α =0.93; CR: 0.95; AVE: 0.83)	5.03	1.31
	We continuously examine innovative opportunities for the strategic use of business analytics.		
	We enforce adequate plans for the utilization of business analytics.		
	We perform business analytics planning processes in systematic ways.		
	We frequently adjust business analytics plans to better adapt to changing conditions.		
	Decision-making (DM) (α =0.92; CR: 0.94; AVE: 0.75)	5.13	1.16
	When we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work.		
	When we make business analytics investment decisions, we project how much these options will help end users make quicker decisions.		
	When we make business analytics investment decisions, we estimate whether they will consolidate or eliminate jobs.		
	When we make business analytics investment decisions, we estimate the cost of training that end users will need.		
	When we make business analytics investment decisions, we estimate the time managers will need to spend overseeing the change.		
	Coordination (COD) (α =0.91; CR: 0.94; AVE: 0.79)	5.011	1.215
	In our organization, business analysts and line people meet regularly to discuss important issues.		

	In our organization, business analysts and line people from various departments regularly attend cross-functional meetings.		
	In our organization, business analysts and line people coordinate their efforts harmoniously.		
	In our organization, information is widely shared between business analysts and line people so that those who make decisions or perform jobs have access to all available know-how.		
	Control (COL) (α =0.93; CR: 0.95; AVE: 0.82)	5.29	1.21
	In our organization, the responsibility for analytics development is clear.		
	We are confident that analytics project proposals are properly appraised.		
	We constantly monitor the performance of the analytics function.		
	Our analytics department is clear about its performance criteria.		
	Our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process.		
	Our company is better than competitors in reducing cost within a business process.		
	Our company is better than competitors in bringing complex analytical methods to bear on a business process.		
	Our company is better than competitors in bringing detailed information into a business process.		
BDA personnel expertise (Kim et al., 2012)	**Sub-dimensions**	**Mean**	**SD**
	Technical knowledge (TK) (α =0.94; CR: 0.95; AVE: 0.80)	5.12	1.24
	Our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE tools, etc.).		
	Our analytics personnel are very capable in terms of managing project life cycles.		
	Our analytics personnel are very capable in the areas of data management and maintenance.		
	Our analytics personnel are very capable in the areas of distributed computing.		
	Our analytics personnel are very capable in decision support systems (e.g., expert systems, artificial intelligence, data warehousing, mining, marts, etc.).		
	Technological management knowledge (TMK) (α =0.91; CR: 0.94; AVE: 0.78)	5.19	1.17
	Our analytics personnel show superior understanding of technological trends.		
	Our analytics personnel show superior ability to learn new technologies.		
	Our analytics personnel are very knowledgeable about the critical factors for the success of our organization.		
	Our analytics personnel are very knowledgeable about the role of business analytics as a means, not an end.		
	Business knowledge (BK) (α =0.91; CR: 0.94; AVE: 0.80)	5.23	1.20
	Our analytics personnel understand our organization's policies and		

	plans at a very high level.		
	Our analytics personnel are very capable in interpreting business problems and developing appropriate solutions.		
	Our analytics personnel are very knowledgeable about business functions.		
	Our analytics personnel are very knowledgeable about the business environment.		
	Relational knowledge (RK) (α =0.91; CR: 0.94; AVE: 0.79)	5.30	1.14
	Our analytics personnel are very capable in terms of managing projects.		
	Our analytics personnel are very capable in terms of executing work in a collective environment.		
	Our analytics personnel are very capable in terms of teaching others.		
	Our analytics personnel work closely with customers and maintain productive user/client relationships.		
Process-oriented dynamic capabilities (Kim et al., 2011)	**Constructs**	**Mean**	**SD**
	Process-oriented dynamic capabilities (PODC) (α =0.88; CR: 0.92; AVE: 0.74)	5.192	1.219
	Our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process.		
	Our company is better than competitors in reducing cost within a business process.		
	Our company is better than competitors in bringing complex analytical methods to bear on a business process.		
	Our company is better than competitors in bringing detailed information into a business process.		
Firm performance (Tippins and Sohi, 2003) (Wang et al., 2012)	**Sub-dimensions**	**Mean**	**SD**
	Financial performance (FP) (α =0.93; CR: 0.95; AVE: 0.78): Using analytics improved ____ during the last 3 years relative to competitors:	5.55	1.07
	________Customer retention		
	_________Sales growth		
	__________Profitability		
	__________Return on investment		
	__________Overall financial performance		
	Market performance (MP) (α =0.90; CR: 0.93; AVE: 0.77): Using analytics improved ____ during the last 3 years relative to competitors	5.34	1.09
	______We have entered new markets more quickly than our competitors		
	______ We have introduced new products or services to the market faster than our competitors.		
	______Our success rate of new products or services has been higher than our competitors.		
	______Our market share has exceeded that of our competitors.		

*Table 4. Standardized loadings of the latent constructs in the model (***p < 0.001)*

First-Order Constructs	Indicators	Loadings	Second-order constructs and their loadings	Third-order construct and loadings
Business Knowledge (BK)	BK1	0.85***	Personnel Expertise Capability (0.90-0.94)	Big Data Analytics Capability (0.93-0.96)
	BK2	0.89***		
	BK3	0.92***		
	BK4	0.91***		
Relational Knowledge (RK)	RK1	0.91***		
	RK2	0.90***		
	RK3	0.89***		
	RK4	0.87***		
Technical Knowledge (TK)	TK1	0.87***		
	TK2	0.90***		
	TK3	0.91***		
	TK4	0.90***		
	TK5	0.90***		
Technological management knowledge (TMK)	TMK1	0.89***		
	TMK2	0.88***		
	TMK3	0.90***		
	TMK4	0.87***		
Connectivity (CN)	CN1	0.80***	Infrastructure Capability (0.90-0.92)	
	CN2	0.88***		
	CN3	0.90***		
	CN4	0.79***		
Compatibility (CP)	CP1	0.88***		
	CP2	0.92***		
	CP3	0.89***		
	CP4	0.90***		
Modularity (MOD)	MOD1	0.89***		
	MOD2	0.92***		
	MOD3	0.90***		
	MOD4	0.73***		
Coordination (COD)	COD1	0.90***	Management Capability (0.93-0.94)	
	COD2	0.89***		
	COD3	0.90***		
	COD4	0.88***		
Control (COL)	COL1	0.89***		
	COL2	0.92***		
	COL3	0.91***		
	COL4	0.91***		
Decision-making(DM)	DM1	0.87***		
	DM2	0.87***		
	DM3	0.84***		
	DM4	0.87***		
	DM5	0.89***		
Planning (PLAN)	PLAN1	0.90***		

	PLAN2 PLAN3 PLAN4	0.92^{***} 0.92^{***} 0.91^{***}		
Financial Performance (FP)	FP1 FP2 FP3 FP4 FP5	0.84^{***} 0.87^{***} 0.91^{***} 0.90^{***} 0.90^{***}	0.84-0.91	-
Market Performance (MP)	MP1 MP2 MP3 MP4	0.89^{***} 0.89^{***} 0.92^{***} 0.81^{***}	0.81-0.92	-
Process-oriented Dynamic Capabilities (PODC)	PODC1 PODC2 PODC3 PODC4	0.90^{***} 0.89^{***} 0.93^{***} 0.89^{***}	-	-

We also tested whether the principal factor accounted for the majority of the variance explained in order to identify a potential common method bias (Podsakoff and Organ, 1986). The first factor accounted for 57% of total variance; this result is a bit high and indicates that there is a possibility of common method bias. However, the correlation matrix (Table 5) shows that the highest inter-construct correlation is 0.83, while common method bias is usually evidenced by extremely high correlations (r>0.90) (Bagozzi et al., 1991). Therefore, common method bias is not a serious issue in this research. To check for multicollinearity, collinearity diagnostics for constructs were also conducted. The analysis shows that the collinearity indicator –variance inflation factor –falls below the acceptable cut-off point (VIF<5) (Hair et al., 2006), suggesting that multicollinearity is not an issue in our study. Finally, we estimated the goodness of fit ($\sqrt{\overline{communality} \times \overline{R}^2}$) following Tenenhaus et al. (2005) for PLS path modelling and the results show that the model has adequate goodness-of-fit as it exceeds 0.36 suggested by Wetzels et al. (2009).

Table 5. Inter-correlations of the first-order latent constructs

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	CN	**0.84**													
2	CP	0.40	**0.89**												
3	MOD	0.44	0.44	**0.86**											
4	PLAN	0.41	0.34	0.37	**0.91**										
5	DM	0.49	0.35	0.36	0.53	**0.87**									
6	COD	0.45	0.44	0.46	0.55	0.52	**0.89**								
7	COL	0.40	0.35	0.41	0.48	0.53	0.53	**0.90**							
8	TK	0.43	0.44	0.49	0.39	0.37	0.46	0.45	**0.91**						
9	TMK	0.45	0.49	0.48	0.38	0.43	0.45	0.46	0.51	**0.89**					
10	BK	0.46	0.47	0.39	0.37	0.40	0.43	0.41	0.42	0.55	**0.89**				
11	RK	0.48	0.41	0.30	0.35	0.40	0.42	0.44	0.48	0.51	0.51	**0.89**			
12	PODC	0.44	0.49	0.33	0.37	0.35	0.43	0.36	0.46	0.48	0.49	0.42	**0.86**		
13	FP	0.35	0.37	0.37	0.31	0.39	0.47	0.37	0.35	0.47	0.45	0.42	0.44	**0.88**	
14	MP	0.32	0.38	0.44	0.38	0.30	0.42	0.35	0.34	0.36	0.35	0.38	0.37	0.49	**0.88**

Notes: CN-Connectivity; CP-Compatability; MOD-Modularity; PLAN-Planning; DM-Decision Making; COD-Coordination; COL-Control;TK-Technical Knowledge; TMK-Technological Management Knowledge; BK-Business Knowledge; RK-Relational Knowledge; PODC-Process-oriented dynamic capabilities; FP-Financial Performance; MP-Makret Performance;

The bold values on the diagonal line are the square roots of AVE.

6.2 Structural Model

The structural model indicates that BDAC and PODC enhanced FPER, with path coefficients of 0.56 ($p < 0.001$) and 0.28 ($p < 0.01$) respectively, explaining 65% of the variance. BDAC enhanced PODC, with a path coefficient of 0.84 ($p < 0.001$), explaining 70% of the variance. Thus, all three hypotheses, H1 to H3, were supported as the path coefficients were significant at $p < 0.001$. In sum, the R^2 scores for all dependent variables (FPER: 65%; PODC: 70%) explained by the research model were significantly large according to the effect sizes defined for R^2 by Cohen (1988) and (Chin, 2010b).

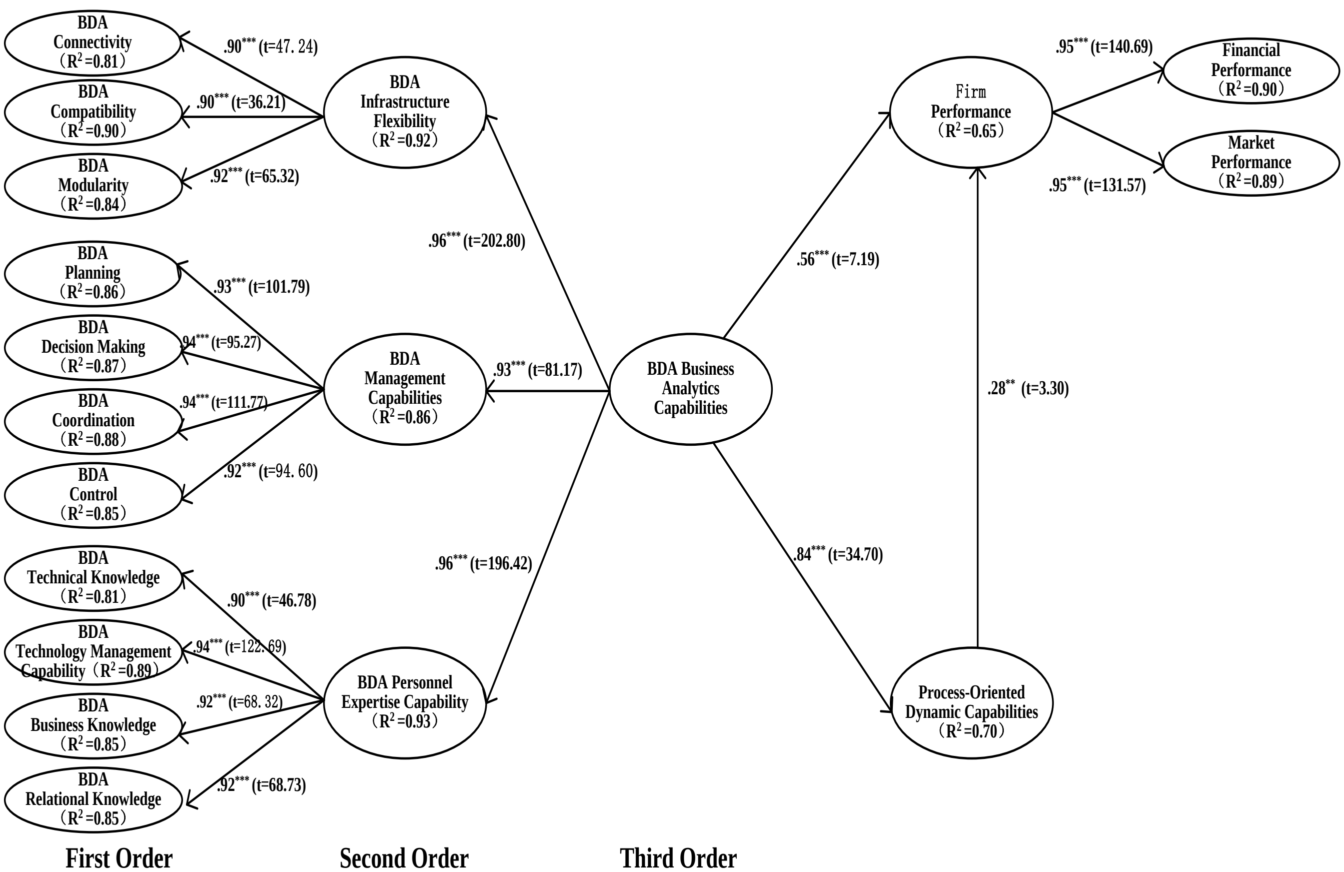

Figure 2. Full structural model

*Note: ***p < 0.001, **p<0.01,*

6.3 Test for Mediating Effects

Our proposed research model includes potential mediation effects. Specifically, PODC may mediate the impact of BDAC on FPER. The procedure for mediation analysis is based on the path coefficients and standard errors of the direct paths between (i) independent and mediating variables (i.e., iv→m), and (ii) mediating and dependent variables (i.e., m→dv). The results of the PLS analysis are used to calculate the extent to which a construct mediates the relationship between the independent variable and the dependent variable (Hoyle and Kenny, 1999). In this study, the magnitude of the mediation effect between BDAC (iv) and FPER (dv) mediated by PODC (m) is the product of the standardized paths between iv and m and between m and dv. The standard deviation of the mediated path can be computed based on the magnitudes and the variance of the paths among iv, m, and dv. The results of the analyses of paths in the model are shown in Table 6. The results showed that PODC mediated BDAC and FPER with a z statistic of 3.19 using the Sobel test.

Table 6. Significance of mediated paths

Indirect Effect	Mediated Path	Path Coefficient	Z Statistic
BDAC→FPER	BDAC→PODC→FPER	0.235	3.19**

a. Statistic is significant at **p<0.01.
b. The standard error of the mediated path is approximated based on the formula sqrt($b^2S_a^2 + a^2S_b^2 + S_a^2S_b^2$), where a and b are the magnitudes of the paths between iv, m, and dv, and S_a and S_b are the standard deviations of a and b.

7 CONCLUSION

The primary objective of this study was to examine the direct impact of BDAC on FPER, as well as the mediating effects of PODC on the relationship between BDAC and FPER. The results show that all the causal links posited by our model are supported. More specifically, both BDAC and PODC explain 65% of the variance of FPER in which 30% of the variance is explained by the mediator. The study estimated the size of the indirect effect using variance accounted for (VAF) value, which indicates the ratio of the indirect effect to the total effect (0.84*0.28/0.84*0.28+0.56). The findings show that the higher-order BDAC construct has a stronger effect on FPER than the PODC. However, PODC appears to be a significant partial mediator, which suggests improving both BDAC and PODC in order to enhance FPER. Among all the dimensions of BDAC, infrastructure and personnel capabilities (β=0.96) were relatively more important than management capability (β=0.93). Although we identified these differences in measuring the importance of BDAC dimensions, we should note that the magnitude of differences are very small, thus all the dimensions should be given equal importance in building BDAC. The findings also show that second-order constructs have significant positive association with their corresponding first order components. For instance, infrastructure capability was reflected by connectivity (β=0.90), compatibility (β=0.90) and modularity (β=0.92) in which modularity reflects the highest variance (85%) of infrastructure capability. Accordingly, variance of management capability and personnel capability were calculated to reflect their corresponding components (See Fig. 2). Overall, the nomological validity of the study was ensured as the findings show that BDAC has a significant positive impact on both PODC (R^2 =0.70) and FPER (R^2 =0.65) in which PODC was recognized as a strong mediator.

7.1 Implications for Research

This study has several theoretical implications for BDAC research. First of all, it is among the first studies to assess the impact of BDAC on firm performance and process-oriented dynamic capabilities and evaluate the mediation effect of PODC on the relationship between BDAC and FPER. Although there is a rich body of literature on BDAC (Kim et al. 2012) and PODC (Kim et al. 2011), research on integration of the two constructs is scant. The role of BDAC on FPER emerges clearly from the previous literature. What is less understood is the mediating effect of PODC on BDAC's impact on FPER. Hence, our study tested the mediating effect on BDAC and FPER using data gathered from Chinese firms. This study also integrates BDAC and PODC in a single model and reconciles what had previously been assumed to be independent constructs. In the existing literature, the combined effects of BDAC and PODC have rarely been studied. Finally, by adopting the approach of decomposing BDAC into three constructs, as shown in the theoretical model (see Figure 1), we show that this method helps to understand the linkage between BDAC and FPER.

7.2 Implications for Practice

Many of our findings provide guidance to managers and consultants who are engaged in implementing BDAC in firms. The mediating role of PODC clearly highlights how, in uncertain environments, BDAC can be leveraged as a source of sustainable competitive advantage. Conversely, if PODC is missing, then BDAC, which may be effective in the present scenario, can lose its competitive advantage, given that the business environment is highly dynamic in nature. The findings that the three BDAC components strongly influence firms' performance indicates that, in order to translate BDAC into firm performance, managers need to concentrate on infrastructure capability, which includes BDA connectivity, compatibility and modularity. Similarly, managers may examine the microstructure of BDA planning, investment, coordination and control. This helps to ensure BDA management capability, which is one of the pillars of BDAC. Finally, the most important pillar of BDAC is BDA personnel expertise capability. To strengthen this aspect of BDAC, an organized effort must be made to build technical knowledge, technological management knowledge, business knowledge and relational knowledge related to BDA. We recognize that the idea of recommending that organizations embrace the three-pillar strategy of BDAC may sound highly theoretical. However, this conclusion is based on our findings from the data.

7.3 Limitations and Future Research

We believe that our model is sound and firmly grounded in theory and we have tested it with reliable survey instruments and data. Nevertheless, some limitations and unanswered questions must be addressed. First, we conducted the study within the specific domain of big data analytics and in one context. Although BDA by its nature is context-specific due to the variations in analytics industry, replications of the conceptual model in other settings would enhance its generalizability. Second, we tested our model using cross-sectional data, thus we recommend retesting the findings using panel data to investigate its stability. Third, in our study we adopted perceptual performance measures, which could be replaced by objective measures to present a concrete picture of BDAC's impact on firm performance. Fourth, we recommend developing context specific BDAC instrument (e.g., customer analytics, supply chain analytics etc.) through rigorous scale validation procedure in order to better measure BDAC for various industries. Finally, we did not investigate the impact of organizational culture and top management commitment on the implementation of BDAC in a firm, which could be taken into account as moderating variables to extend knowledge in big data economy.

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