Journal of Business Research 96 (2019) 228–237

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Business analytics and firm performance: The mediating role of business process performance

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ARTICLE INFO

Keywords:
Business analytics
Business process performance
Firm performance
Resource-based view
Turkey

ABSTRACT

Due to the rapidly increasing popularity of business analytics (BA), investigation of the antecedents/determinants of the adoption of BA and the subsequent impact of the same to the firm performance has become an important research topic. Drawing on the fundamentals of the resource-based view (RBV), this study proposes a model that examines the effects of the BA adoption on business process performance (BPER) and the mediating role that BPER plays in the relationship between the adoption of BA and firm performance (FP). Based on the data collected from 204 medium- to high-level business executives in various industries, the results of this empirical study indicate that the adoption of BA positively influences BPER. There is also positive relationship between BPER and FP. Finally, the results show that BPER fully mediates the relationship between BA adoption and FP.

1. Introduction

Rapidly changing globalized business environment coupled with the unprecedented advancements in technology fronts enforce firms to become more innovative and agile in the way they identify and respond to their customers' evolving needs and wants. Success or mere survival depends on these businesses' ability to effectively/accurately and efficiently/quickly respond to the complex dynamics in the global marketplace. Thus, information systems (IS) and information technologies (IT) become the metaphors that provide different tools and techniques to the businesses that intend to overcome the challenges of these environments (Sharda, Delen, & Turban, 2016). Recently, firms have been able to access to huge data generated through their operations undertaken in electronic platforms. It is also worthwhile to recognize the role of IT penetration into businesses to generate more digitalized firms that collect various types of structured and unstructured data. Availability and accessibility of these large data sets foster the importance of IS/IT techniques to understand the business environment and markets for the firms striving for making meaningful business decisions to create a competitive advantage (Bichler, Heinzl, & van der Aalst, 2017; Sharma, Mithas, & Kankanhalli, 2014).

IS have numerous applications that involve various tools and techniques to deal with the processing of extensive data sets. To add value and to support/drive decisions for businesses, these tools and techniques statistically and quantitatively analyze a huge collection of data sources, and are collectively called business analytics (BA) nowadays (Delen & Zolbanin, 2018). They are aimed at dealing with the big data phenomenon (ever-increasing volume, variety, and velocity of data) compiled by organizations and also end users (Sharda et al., 2016). Largely due to its promise, investments on the BA enablers are constantly and exponentially growing in recent years, and the expenditures to these tools by businesses have been reaching billions of dollars. They are among the most prioritized expense-worthy tools and applications by especially medium-level and high-level managers (Cosic, Shanks, & Maynard, 2015). According to the study conducted by Accenture and General Electric, 89% of firms believe that they might lose their market if they do not adopt big data and BA (Columbus, 2014). Despite this growing popularity of BA, there is an ambiguity about how the

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https://doi.org/10.1016/j.jbusres.2018.11.028
Received 9 October 2018; Received in revised form 14 November 2018; Accepted 16 November 2018

adoption of BA impacts firm performance (FP) (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Ramanathan, Philpott, Duan, & Cao, 2017; Sharma et al., 2014; Troilo, Bouchet, Urban, & Sutton, 2016).

The current study essentially aims at investigating the relationship between BA adoption and FP. In the adoption of BA tools and applications, three progressive levels/tiers of BA capabilities are suggested by INFORMS (Institute for Operations Research and Management Science): descriptive (DESC), predictive (PRED), and prescriptive (PRES). In addition to these three levels, data acquisition and processing (DACQ) is also included as the forth, and perhaps one of the most fundamental enabler components in the BA framework. Although, there have been many attempts to study and measure the relationships between the adoption of BA and FP (Klatt, Schlaefke, & Moeller, 2011; Sharma et al., 2014; Troilo et al., 2016), the proposed approach differs in the way it concentrates on the overall efficiency and effectiveness of the resources used by the organizations based on the underlying premises of the resource-based view (RBV), wherein the main focus is to investigate the mediating role of business process performance (BPER) between BA adoption and FP. Furthermore, this study also investigates and reports on the potential impact of DACQ on FP within the context of facilitating big data adoption and implementation.

The remainder of this study is organized as follows. Next, we provide a theoretical background to explain our hypotheses. Then, we present our research methods followed by the results of our study. Finally, a conclusion is set out along with the managerial implications and future research suggestions.

2. Theoretical background and hypotheses

According to Wójcik (2015), a competitive business strategy in the future will concentrate on organizational renewal capability, where BA enhancing learning experience and adopting the knowledge discovered may lead the organizations to revitalize their businesses and gain significant performance improvements (Ramanathan et al., 2017). Therefore, under the RBV, the adoption of BA applications and their links with BPER and FP are discussed in the ensuing subsections.

2.1. Resource-based view (RBV) and business analytics (BA)

The RBV is mainly built around the idea of developing abilities to utilize resources for the achievement of competitive advantage (Barney, 1991; Cosic et al., 2015; Delen & Zolbanin, 2018; Gunasekaran et al., 2017). Some organizations are more successful than others in the process of resource accumulation and resource deployment to create distinct capabilities (Peppard & Ward, 2016). To gain sustainable competitive advantage through these distinctive capabilities, resources should be valuable, inimitable, rare, and non-substitutable (VIRN) (Cosic et al., 2015; Gunasekaran et al., 2017; Wójcik, 2015). In terms of BA adoption, data are considered as one of the key resources for an organization to capture, harness, and understand its business operations to improve.

Therefore, operational systems are equipped with applications for DACQ as VIRN resources (Sharda et al., 2016). As noted earlier, DACQ is accepted as one of the indicators of BA adoption and mobilizes a distinctive set of capabilities to generate a sustainable competitive advantage for organizations (Wamba et al., 2017), even though it originates from traditional/structured and modern/unstructured data sources altogether (Appelbaum, Kogan, Vasarhelyi, & Yan, 2017). In addition, the quality of data is an important and invaluable business resource (Appelbaum et al., 2017) for BA, where one of the premises of RBV is to provide distinctive data accuracy (Chae, Yang, Olson, & Sheu, 2014).

For organizations adopting BA, the challenge is to establish a capability to constantly identify opportunities to leverage the businesses (Peppard & Ward, 2016). Hence, continuous change is conceptualized by renewing and reconfiguring resources with the implementation of other BA components; namely, PRES, PRED, and DESC analytics. According to the theory of RBV, the capacity of an organization to proactively create, extend, or modify its resource base through the successful implementation of BA applications influences its promises for creating business value and competitive advantage (Vidgen, Shaw, & Grant, 2017). Therefore, we postulate that a discourse on RBV is relevant and useful to expose how adopting BA leads to resource exploitation with PRES, PRED, and DESC in order to establish a link between business processes and FP with the perception of RBV on DACQ.

BA covers a broad range of applications, technologies, and processes related to collecting, storing, retrieving, and analyzing big data (Bayrak, 2015). As a part of the BA development process, big data indicate the complexity of the unstructured huge amount of data that are only possible to analyze and understand with special tools, such as BA (Bayrak, 2015). Chae et al. (2014) pointed out that BA extensively used data, statistical and quantitative analysis techniques, as well as explanatory and PRED models using mathematical and computer-based algorithms to gain insight about business operations (Appelbaum et al., 2017). BA helps to build up a fact-based management system (Bayrak, 2015; Holsapple, Lee-Post, & Pakath, 2014), and it is explained as a set of business and technical activities with a collection of tools for manipulating, mining, and analyzing environments (Sharda et al., 2016; Sun, Strang, & Firmin, 2017). Hence, we structured the adoption of BA applications in line with the literature.

Our BA model representation is used to identify leverage points with the applications that are most likely to lead to the creation of value and the best use of limited resources for businesses (Hindle & Vidgen, 2018). The four types of analytics (i.e., PRES, PRED, DESC, and DACQ) are employed in the BA model (Bayrak, 2015; Sharda et al., 2016; Sun et al., 2017). Analytical models of BA applications are interconnected with each other with a certain level of overlap, and follow one another in a progressive manner. DACQ is an application that extracts data from new and old/legacy systems, from internal and external sources, and consolidate, summarize, and load them into various types of BA tools/applications (Sharda et al., 2016). The continuous cycle of DACQ to business processes is among the most critical chains that convert data from different sources into consolidated data towards actionable insight/information (Delen, 2015). Therefore, in this study, DACQ-related IS applications are included as a part of the BA adoption model, such as information propagation, data warehousing, data capturing, and document management systems.

DESC analytics addresses the happening that have occurred or are occurring in the organization and underlies essential trends and relationships (Sharda et al., 2016). DESC drills down into historical data to reveal details about "what happened" and hence delivers significant insight/knowledge about BPER. DESC also has the capability of continuously monitoring certain indicators much like an alert system where new transactions are benchmarked against the thresholds established from historical data (Appelbaum et al., 2017). Sivarajah, Kamal, Irani, and Weerakkody (2017) asserted that the DESC model has been implemented with IS applications, such as dashboards, scorecards, data visualization, and online analytical processing (OLAP), to monitor business transactions for some time.

Implementation of PRED analytics comes after DESC and focuses on the prediction of the future using some statistical models and data mining tools and applications (Delen, 2015). PRED analytics technique takes the knowledge acquisition from DESC applications in order to predict behavioral movements of probable future events with an algorithmic analysis (Sharda et al., 2014; Tan, Guo, Cahalane, & Cheng, 2016; Appelbaum et al., 2017). PRED applications are the ones that bring big data into expressive, operational business information (Bayrak, 2015). In our model, we characterized PRED as IS applications, such as market intelligence, investment intelligence, data mining, and decision support systems.

PRES analytics, as an adoption level of the BA model, is defined as a mathematical technique that determines an optimum set of alternative methods or decisions for a given complex situation (Bayrak, 2015). It also designs and creates new innovations while allocating resources to them with a proper justification (Hindle & Vidgen, 2018; Sun et al., 2017). PRES requires highly specialized mathematical modeling techniques capable of handling multi-criteria/multi-objective decision situations to propose/prescribe recommendations to business managers/functions in deciding "what to do next" in a specific situation (Sharda et al., 2014; Pape, 2015). Because of their capacity to respond to "so what" and "now what" questions and their ability to improve service levels, while declining the expenditures (Sivarajah et al., 2017), data analysis, product development, and e-commerce systems are embedded into PRES in our model as the most common IS tools and applications.

Consequently, DACQ, DESC, PRED, and PRES applications were designed to be the components of the BA model to explain how the adoption level of BA applications and their usage influence FP through the mediating effect of BPER.

2.2. Adoption of BA and BPER

Firms can achieve significant performance gains if BA is adopted to align with business processes and objectives of firms (Ramanathan et al., 2017). Business process is a multi-disciplinary and complex situation that receives knowledge from all operations and resources. Thus, analyzing interactions and identifying potential improvements in support of decision-making increases BPER. As one of the BA components, big data that are embedded in DACQ applications enhance business performance and efficiencies by sharing seamless data and information among business processes and external partners. Thus, adoption of BA provides common tools to support, diagnose, and improve the BPER of an enterprise (Sharma et al., 2014; Sun et al., 2017).

Even though there are many studies stating that BA capabilities and applications provide better business value, leading to organizational performance (Bayrak, 2015; Tan et al., 2016), other studies focus directly on the impact of BA in the decision-making performance without considering its impact on business processes (Appelbaum et al., 2017; Cosic et al., 2015; Gunasekaran et al., 2017; Ramanathan et al., 2017; Sun et al., 2017). However, through structure and process changes in a firm, BA and its applications have a wider impact on business value and business processes. Therefore, our study focuses on the adoption of BA applications along with all components, and we propose the following hypothesis regarding the relationship between the adoption of BA applications and BPER.

H1. Adoption of business analytics (BA), which is characterized by data acquisition and processing (DACQ) (i.e., big data), descriptive (DESC), predictive (PRED), and prescriptive (PRES) analytics, positively influences business process performance (BPER).

2.3. BPER and FP

Business processes are all about how an organization manages its key operations that lead to business growth and success (Mithas, Ramasubbu, & Sambamurthy, 2011). Firm-level measurements are the aggregation of various process outcomes that directly impact the FP (Bhatt & Grover, 2005). BPER includes financial and non-financial flexibility, reliability, responsiveness, and cost or asset instruments (Bernhard, Peter, Zoltan, & Maria-Luise, 2006). The performance indicators of business processes should be harmonized with firms' objectives (Bisogno, Calabrese, Gastaldi, & Levialdi Ghiron, 2016). Operational excellence is seen as an integrated performance indicator of a firm that assesses its responsiveness to the customer expectations, its productivity in its business processes, and its sustainability to compete in the market (Wu, Straub, & Liang, 2015). Investments to the business processes may improve their performances; therefore, investments enable firms to increase their output quality (Brynjolfsson & Hitt, 2000). BPER also includes operational effectiveness that is expected to translate into FP (Elbashir, Collier, & Davern, 2008). The clear justification of the relationship between BPER and FP leads us to propose the following hypothesis.

H2. Business process performance (BPER) positively influences firm performance (FP).

2.4. The mediating role of BPER

Many of the previous studies indicate that there is a link between the adoption of BA and FP, in terms of increased business value and competitive advantage (Cosic et al., 2015; Elbashir et al., 2008; Ramanathan et al., 2017). However, investing in BA technologies, of course, has a capacity to improve FP (Larson & Chang, 2016; Troilo et al., 2016). With invaluable data as a strategic resource for an enterprise, the adoption of BA supports business decision-making. At the same time, there is a significant direct link between business processes and adoption of BA that also impacts tangible and intangible performances of the firms (Sun et al., 2017). Furthermore, in order to receive relevant, accurate, and valuable information to manage day-to-day processes as well as strategic initiatives in a highly fluctuated business environment, IS capabilities supported with BA applications need to be utilized to improve the overall performance of a firm. High-quality data is also an important asset that has a big impact on FP (Appelbaum et al., 2017).

Critical success factors, such as organization, process, and technology for the adoption of BA, help to align businesses with BA applications to achieve high business value (Larson & Chang, 2016). Moreover, BA adoption increases creativity in a firm, encourages a collective business environment and knowledge sharing in a more realistic way. BA applications move an organization into an evidence-based problem-solving organization, which obviously supports its performance. The rationale of using and adopting BA applications is to have a better overall organizational performance to achieve competitive advantage through supporting organization's goals better and improving processes for a superior customer satisfaction (Holsapple et al., 2014). The holistic BA applications promote critical interdependencies among inputs, processes, and outcomes so that they create a causal link between BPER and FP. It is believed that BA can improve FP when appropriately adopted (Klatt et al., 2011). However, there is a paucity of research about linkages between the adoption of BA applications and FP with the inclusion of BPER (Appelbaum et al., 2017). Thus, we posit that BPER serves as a mediator between the adoption of BA and FP.

H3. Business process performance (BPER) plays a mediating role in the influence of adopting business analytics (BA), which is characterized by data acquisition and processing (DACQ), descriptive (DESC), predictive (PRED), and prescriptive (PRES) analytics, on firm performance (FP).

3. Research method

3.1. Survey instrument, sample and data collection

The primary data for our study were collected through a cross-sectional postal survey using a questionnaire. The development of the measurement items, the design, and the structure of the questionnaire were in line with the guidelines in prior research (Dillman, 2007). Relying on a review of relevant literature (e.g. Bayraktar, Demirbag, Koh, Tatoglu, & Zaim, 2009; Laudon & Laudon, 2013; Sharda et al., 2014; Ramanathan et al., 2017; Hindle & Vidgen, 2018), the survey questionnaire was arranged to measure the underlying components of adopting BA applications: DACQ, DESC, PRES, and PRED. Likewise, relying on the extant literature, endogenous constructs were identified as BPER and FP.

To establish the content validity of the measures used in this study, the procedure suggested by Hair, Money, Samouel, and Page (2007) was adopted. First, in-depth interviews were undertaken with three chief technology officers (CTOs) in Turkey, who provided us their views of the issues on business analytics based on their actual knowledge and experience. Second, an initial version of the survey questionnaire was revised based on discussions with several expert academics. Finally, a pre-test was conducted with six business professionals that provided eventual fine-tuning opportunities to develop an informative, clear, and well-structured survey questionnaire.

The survey questionnaire was developed in English originally. Its final version was translated into Turkish, and then back-translated into English to ensure accuracy in translation. Prior to administration of the survey questionnaire, an approval of the university's Research Ethics Committee with whom the lead researcher is affiliated, was obtained.

We sampled a range of firms from several product-intensive industries located in Turkey to attain a high level of external validity and generalizability of the research findings. The respondent firms were selected among medium-sized and large-sized firms, as the small-sized firms mostly lack required resources to invest in BA tools and applications. The targeted respondents who would fulfill the surveys were asked to be senior and executive managers or medium-level managers who must have sufficient knowledge of the entire firm and involve highly with the decision-making processes. A cover letter of the survey clearly indicated the required profile for an acceptable respondent. The respondents who did not meet these criteria were eliminated during the data evaluation process.

The sampling frame was formed from the members of the TOBB (Union of Chambers and Commodity Exchanges of Turkey). The TOBB database covers 365 local chambers of commerce, maritime commerce, and commodity exchange with over one million firms. Following the elimination of firms that did not meet the selection criteria, we randomly sampled 800 firms from this database. Following two waves of data collection and one reminder, a total of 235 questionnaires were returned; of which 204 were usable, representing an effective response rate of 25.5%.

The potential of non-response bias was tested by comparing survey results of the early respondents with late respondents who needed a reminder and/or a longer time to respond to the survey (Armstrong & Overton, 1977). Through a *t*-test, we first compared the responses from early and late respondents to our survey and found no statistically significant differences ($p > 0.05$). Second, a comparison of a randomly selected group of 100 non-respondent firms with 204 respondent firms revealed no significant differences for any organizational level indicators (e.g., annual sales, years of operation and number of employees). Hence, no evidence was found for non-response bias. A summary of the characteristics of the sample is shown in Table 1.

Table 1
Characteristics of the sample.

Characteristics		Number	%
Respondent position	Senior/executive manager	106	52
	Middle/first line manager	98	48
Number of employees	< 250	93	46
	251–500	24	12
	501–1000	21	10
	1001–5000	42	21
	> 5000	24	12
Years of operation	< 5 years	8	3.9
	5–10	26	13
	11–30	107	53
	31–50	33	16
	> 50	30	15
Annual revenue (Turkish Lira)	< 25 million	34	17
	25 million–99 million	44	22
	100 million–249 million	26	13
	250 million–499 million	19	9.3
	Equal or > 500 million	81	40
Industry sectors	Food and beverages	16	7.8
	Durables, consumer electronics and machinery	22	11
	Chemicals, pharmaceutical and plastics	15	7.4
	Textile, leather and clothing	26	13
	Other manufacturing	8	3.9
	Investment, banking and finance	22	11
	Transportation, telecommunication and media	15	7.4
	Information systems and technology services	23	11
	Construction and real estate	11	5.4
	Health and social services	12	5.9
	Wholesale and retail	22	11
	Other services	12	5.9
N =		204	

3.2. Measurement of variables

The study is composed of three main constructs and control variables. The constructs were measured through five-point Likert scales. The adoption of BA was measured, ranging from 1 ("never") to 5 ("always"), which explains the level of adoption. BPER and FP were measured, ranging from 1 ("strongly disagree") to 5 ("strongly agree").

3.2.1. Adoption of BA

Adopting BA applications were operationalized in terms of four underlying sub-constructs: DACQ, PRES, PRED, and DESC. Each construct with its related applications were adapted from business intelligence studies and the IS literature (Zwass, 1998; Alter, 2002; Laudon & Laudon, 2013; Sharda et al., 2014; Hindle & Vidgen, 2018).

3.2.2. BPER

The items comprising BPER were drawn from earlier studies (Bayraktar et al., 2009; Elbashir et al., 2008; Luo, Fan, & Zhang, 2012; Mahmood & Soon, 1991; Mclaren, Head, Yufe, & Chan, 2011; Mithas et al., 2011) and were as follows: "Our firm has rapid and effective internal and external coordination for its regional, national, and global activities"; "Our firm is successful in gaining economies of scale"; "The productivity of labor has been improved"; "Our customers' requests have been adequately responded"; and "Our meetings and discussions have been held efficiently and effectively."

3.2.3. FP

There is an extensive literature about FP. Hence, it is very difficult to choose a single measurement of FP. The FP adapted here was derived from previous studies on BA and IS (Akter et al., 2016; Bharadwaj, 2000; Duhan, 2007; Glaister, Dincer, Tatoglu, Demirbag, & Zaim, 2008; Mithas et al., 2011; Ordanini & Rubera, 2009; Radhika & Hartono, 2003; Ramanathan et al., 2017; Troilo et al., 2016).

3.2.4. Control variables

The firm specific characteristics were tested with three control variables. First, firm size (SIZE) was measured by the number of employees in an ordinal form, which includes five categories as shown in Table 1. Second, the age of the firm (AGE) was measured by the number of years that a firm has been in operation since its establishment. Five broad age categories were introduced, ranging from "5 years or less" to "more than 50 years". Third, we created two main sectoral categories which included the manufacturing and service sectors. A binary scale was used to measure these industry sectors (IND).

The measurement of the study constructs (with the exact wording of the questions) and their sources are reproduced in the Appendix A.

4. Analysis and results

A confirmatory factor analysis (CFA) was adopted to study the relationships between the constructs. The study examined reflective constructs for the first and second order. There are strong correlations among indicators and the variables, which is why BA constructs were observed as the effects of indicators (Gruber, Heinemann, Brettel, & Hungeling, 2010). First, reliability analysis was tested for each construct. The second test was conducted on the first-order and second-order analysis through structural equation modeling (SEM) using AMOS, which assessed the validity of the factorial structure of the constructs (Byrne, 2001). The whole model was analyzed with SEM to determine whether it offers a good fit to the data. Finally, convergent and discriminant validity were also checked to reveal the validation of data.

4.1. Reliability and validity

To measure reliability, the Cronbach's alpha, which was the reliability coefficient, was checked for each of the constructs. In our study, BA adoption was measured by four sub-constructs. Cronbach's alpha values for these sub-constructs (i.e., DACQ, PRES, PRED and DESC) were found as 0.80, 0.60, 0.86 and 0.88, respectively. In addition, the Cronbach's alpha values of reliability for the underlying constructs of BPER and FP were 0.77 and 0.81, respectively. These results indicate that the construct reliabilities are satisfactory (Hair, Black, Babin, Anderson, & Tatham, 2006). The Cronbach's alpha results for all the constructs are shown in Table 2.

Internal consistency of a set of measures was analyzed with a composite reliability (CR) factor. The threshold value of 0.70 for the CR specifies sufficient reliability for a construct (Fornell & Larcker, 1981). As shown in Table 2, the CR measurements are within the recommended thresholds, and each of the constructs in our study is sufficiently reliable.

The measurement model of variables, which is CFA, began with a first-order analysis to decide whether the adoption of BA was explained by the latent variables of its underlying sub-constructs. Therefore, the first-order model complied to check the goodness of fit indices (GIF) and found that the result was satisfactory (χ^2/d.f. = 1.62, GFI = 0.92, adjusted goodness-of-fit index (AGFI) = 0.88, Tucker–Lewis coefficient (TLI) = 0.96, and the comparative fit index (CFI) = 0.97). The first-order analysis confirms the presence of the four sub-constructs (i.e., DACQ, PRES, PRED, and DESC). However, we had to determine whether these sub-constructs sufficiently explain the adoption of BA. Therefore, a second-order analysis was conducted with reflective indicators. Four items, namely DACQ, PRES, PRED, and DESC, were perceived as products of the BA adoption. The second-order analysis revealed that all of the necessary fit indices were satisfied, and the threshold values were exceeded (χ^2/df = 1.60, GFI = 0.92, AGFI = 0.88, TLI = 0.96, CFI = 0.97). The result of the second-order analysis pointed out that the directions of causality were from the construct to the indicators (Gruber et al., 2010), and the higher-order latent factor for BA adoption governed the correlation among DACQ, PRES, PRED, and DESC (Moon, Yi, & Ngai, 2012). In addition, the efficacy of these two models needs to be checked by comparing the Akaike information criterion (AIC) measurement. The result showed

Table 2
Assessment of measurement model.

Construct	Items	Model SRW[a]	AVE[b]	CR[c]	Cronbach's Alpha
Adoption of business analytics	**BA**				
Data acquisition and processing	***DACQ***	**0.96**	**0.50**	**0.80**	**0.80**
Information propagation	DACQ1	0.68			
Data warehousing	DACQ2	0.69			
Data capturing system	DACQ3	0.79			
Document management system	DACQ4	0.64			
Prescriptive analytics	***PRES***	**0.97**	**0.50**	**0.75**	**0.60**
Data analysis system	PRES1	0.84			
Product development system	PRES2	0.67			
E-commerce	PRES3	0.60			
Predictive analytics	***PRED***	**0.99**	**0.57**	**0.84**	**0.86**
Marketing intelligence system	PRED1	0.65			
Investment intelligence system	PRED2	0.67			
Data mining	PRED3	0.79			
Decision support system	PRED4	0.88			
Descriptive analytics	***DESC***	**0.94**	**0.62**	**0.87**	**0.88**
Visualization	DESC1	0.80			
Scorecard	DESC2	0.79			
Dashboard	DESC3	0.76			
OLAP analysis	DESC4	0.81			
Business process performance	**BPER**	**0.54**	**0.50**	**0.83**	**0.77**
Our firm has rapid and effective internal and external coordination for its regional, national and global activities.	BPER1	0.66			
Our firm is successful in gaining economies of scale.	BPER2	0.69			
The productivity of labor has been improved.	BPER3	0.79			
Our customers' requests have been adequately responded.	BPER4	0.68			
Our meetings and discussions have been held efficiently and effectively.	BPER5	0.70			
Firm performance	**FP**	**0.45**	**0.52**	**0.89**	**0.81**
Our firm has achieved a high level of return on sales.	FP1	0.62			
Our firm's distribution cost has been reduced.	FP2	0.87			
Our firm has increased its market share.	FP3	0.59			
Our firm has achieved a high level of return on investment.	FP4	0.64			
Our firm's administrative expenses have been reduced.	FP5	0.89			
Our firm's inventory cost has been reduced.	FP6	0.82			
Our staff cost has been reduced.	FP7	0.72			
Our firm has achieved a higher level of customer loyalty.	FP8	0.49			

Notes:
*boldface items indicate the group-level labels/categories for the constructs.
[a] Model standardized regression weights are significant at $p < 0.001$.
[b] Average variance extracted.
[c] Composite reliability.

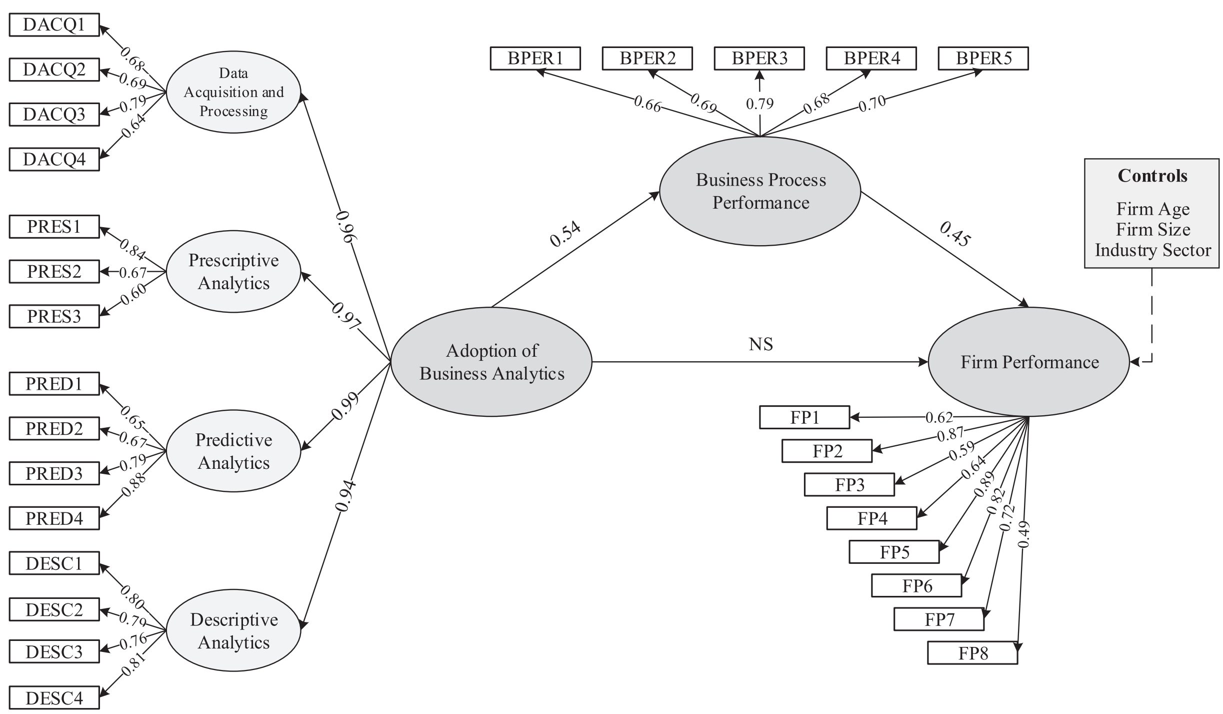

Fig. 1. Relationships between adoption of BA, business process performance and firm performance.
Notes:
*All standardized regression weight are significant at $p < 0.001$.
+ NS: Not significant.

that the second-order AIC measurement (366, 8) was lower than the first-order AIC measurement (377, 69), which indicates that the second-order model holds better parsimony (Moon et al., 2012) and better choices for the entire structural model. We also note that all four sub-constructs (i.e., DACQ, PRES, PRED, and DESC) have positive and significant ($p < 0.001$) standardized regression weights, which are shown in Fig. 1.

The average variance extracted (AVE) estimates were tested to confirm the convergent validity and the scale of reliability for the study. The results indicated sufficient reliability for our constructs by confirming the threshold value of 0.5 (Fornell & Larcker, 1981), as presented in Table 2.

Discriminant validity was measured to differentiate constructs and sub-constructs from each other. The measurement was conducted with nine pairwise tests, and the findings supported the discriminant validity of each pair (see Table 3).

4.2. Hypotheses testing

The descriptive statistics and inter-correlations among the variables are shown in Table 4. There are significant correlations among BA adoption, BPER, and FP constructs. These results proved that BA adoption has an impact on both BPER and FP.

Table 3
Discriminant validity of the measurement model.

Test #	Description	χ^2 model	χ^2 unconstrained model	Difference[a]
1	DESC → PRED	15.55	11.65	3.90
2	DESC → PRES	17.79	11.97	5.82
3	DESC → DACQ	43.59	37.43	6.16
4	PRED → PRES	34.49	19.73	14.76
5	PRED → DACQ	43.48	25.64	17.84
6	PRES → DACQ	40.18	24.27	15.91
7	BA → BPER	294.61	242.11	52.5
8	BA → FP	381.18	312.90	68.28
9	BPER → FP	241.57	167.85	73.72

[a] All values are significant at $p < 0.001$.

Fig. 1 shows the results of the structural model related to our hypotheses. The model parameters were calculated with the maximum likelihood method in SEM. In order to test our hypotheses, whole linkages between the exogenous variable of BA adoption and the endogenous variables of BPER and FP were statistically tested with fit indices. The GFI of the model is satisfactory (χ^2/d.f. = 1.56, $p < 0.001$), as it is within the threshold range between 0 and 3, whereas a lower value implies a better fit. Moreover, the fit indices for the model are highly satisfactory (GFI = 0.85, AGFI = 0.81, TLI = 0.92, CFI = 0.93, RMSEA = 0.065).

Strong support was found for H1 in that the adoption level of BA, which is characterized by DACQ, DESC, PRED, and PRES analytics, positively influences BPER. This finding provides some additional support to an earlier research by Chae et al. (2014), who found a significant relationship between advanced analytics and operational performance. It should also be noted that our finding contradicts with the assertion of Ramanathan et al. (2017), arguing that an implemented right technology or low-level BA cannot guarantee an improvement or may even create a negative impact on business performance.

H2, which posits that BPER has a positive and significant effect on FP ($\beta1 = 0.45$, $p < 0.001$), received strong support. This finding is in line with prior research (Elbashir et al., 2008; Gu & Jung, 2013).

H3 postulates that BPER mediates the relationship between the adoption of BA and FP. In order to check full mediation, the total effect between the adoption of BA and FP was tested without considering other interactions. It was found that the total effect was significant between the adoption of BA and FP ($p < 0.001$). However, the real organizational systems cannot exist without any performance on business processes. Therefore, the proposed model was organized to be tested with three main constructs. Mediation analysis indicated that the adoption of BA had a positive effect on FP only through the mediation role of BPER. A Sobel test was conducted to prove the mediation effect and whether it was statistically significant (Baron & Kenny, 1986). The

Table 4
Descriptive statistics and inter-correlations.

Variables		Definition	Mean	S.D.	1	2	3	4	5	6	7	8	9
1	DACQ	BA: Data acquisition and processing	3.76	0.90	1								
2	PRES	BA: Prescriptive analytics	3.42	0.97	0.61*	1							
3	PRED	BA: Predictive analytics	3.06	1.04	0.73*	0.65*	1						
4	DESC	BA: Descriptive analytics	3.12	1.08	0.72*	0.62*	0.78*	1					
5	BPER	Business process performance	3.99	0.56	0.45*	0.41*	0.42*	0.38*	1				
6	FP	Firm performance	3.62	0.56	0.26*	0.33*	0.30*	0.31*	0.48*	1			
7	SIZE	Firm size	2.41	1.51	0.27*	0.10	0.27*	0.33*	0.78*	0.15	1		
8	AGE	Firm age	3.25	0.98	0.04	0.05	0.04	−0.03	0.02	−0.01	0.33*	1	
9	IND	Industry sector	5.92	3.32	−0.09	−0.1	−0.06	−0.07	−0.03	0.01	−0.10	−0.10	1

* $p < 0.01$.

Sobel test result indicated that there is a significant ($p < 0.001$) support for H3, indicating that BPER serves a mediating role in the relationship between the adoption of BA and FP. Evidently, the adoption of BA is noted to be an important strategic antecedent to create a superior FP (Cosic et al., 2015; Gunasekaran et al., 2017; Troilo et al., 2016).

As for the control variables, AGE and IND were found to be insignificant. Only SIZE was found to have a positive and significant standardized coefficient on FP ($p < 0.05$). It means that large-sized firms show higher FP compared to medium-sized firms.

5. Discussion and conclusions

This study examined the antecedents of BA adoption and a mediating role of BPER in the relationship between BA adoption and FP, relying on a sample of Turkish firms. The findings of the study indicated that there are direct relationships between BA adoption and BPER, and BPER and FP. Nevertheless, indirect relationship between the adoption of BA and FP—through the mediating role of BPER—has also been proven.

The consequent antecedents of BA adoption, which are enterprise applications with embedded BA tools, are proved to have four dimensions. Some of the literature (Delen & Benjamin, 2003; Sharda et al., 2014; Bayrak, 2015; Appelbaum et al., 2017) include only three of them, such as: DESC, PRED, and PRES analytics. However, our study posits that big data (i.e., DACQ and processing) are also a part of the BA adoption that needs to be considered during the implementation. Data without processing applications, as well as BA tools and techniques without data, represent no practical use for the firms. They both complement each other. Otherwise, investment on both technologies would yield no return for the firms, and they will lose their competitive advantage in the market.

Our study contributes to the extant literature that relies on RBV as a foundational and invaluable theory to further managerial research. VIRN, sensing, seizing, and reconfiguring occur in each of the BA applications. These applications that are supported and created by static and dynamic assets of the firms lead them to gain positive performance improvements and help them capture sustained competitive advantage. The results of our empirical study prove this theoretical background by presenting direct relationships between BA adoption and BPER, as well as between BPER and FP, so the mediating role of BPER. Static assets, such as big data technologies, are transferred into dynamic assets through the applications of DESC, PRED, and PRES analytics. This transformation of static capabilities into dynamic ones helps firms proactively create, extend, or modify their resource base, and it enables them to lead business value (Vidgen et al., 2017).

Furthermore, the direct relationship between the BA adoption and BPER proves that the BA algorithms and technologies are integrated with firm processes (Tan et al., 2016). This integration improves a firm's ability to sense and respond to opportunities in the market, and it carries out such knowledge to business processes (Chen, Wang, Nevo, Benitez-Amado, & Kou, 2015).

A direct relationship between BPER and FP is also the result of a deep connection between processes and their outputs. Higher process capabilities improve BPER and FP together (Gu & Jung, 2013). Improved operational performance is central for a firm's responsiveness to market and revenue growth (Rai, Patnayakuni, & Seth, 2006). Thus, our proposition of a direct relationship between BPER and FP is clearly supported by prior literature.

Our study investigates the mediating role of BPER in the relationship between BA adoption and FP. Even though a direct relationship between BA adoption and FP sounds quite natural, there is no direct link between them in reality, so long as an acceptable level of BPER is achieved. This refers to the importance of communicating business knowledge gained and decisions made with the processes properly to accomplish a reasonable performance. An effective use of BA improves the customer orientation and helps in achieving better FP. At the same time, more integration with the other business domains helps to get better FP. Adopting BA applications may not be translated directly into FP; instead, process-level performance may act as a mediator between the BA adoption and FP (Ramanathan et al., 2017). Furthermore, the given framework for BA adoption creates value for a firm because it provides benefits of improving business processes in the accomplishment of the FP through the creation of competitive advantage in the market.

Especially in dynamic and complex business environments, inimitable data through sensible applications of BA help to understand the business dynamics better. Market assumptions may be verified/justified with real data through these BA applications. Strategic orientations may be traced back to verify their validity. Investments on BA applications may speed up task execution times and reduce the errors on the practice. Therefore, operational efficiency is improved with the support of BA applications, and the business processes performance is increased. Likewise, managerial decision-making in all levels may be carried out based on the facts (Klatt et al., 2011). Optimizing the business operations, forecasting the outcomes, improving efficiency, making better decisions, innovating new products and services, and capturing new market opportunities will help firms to gain competitive advantage against their rivals (Bayrak, 2015).

5.1. Limitations and future research

While this study is mainly built on the premises of RBV, there is a significant amount of scope for researchers to investigate the link between BA adoption and firm performance through a variety of theoretical lenses. The intention here is to encourage researchers to take this study forward, for example using institutional theory, stakeholder theory as well as other theoretical perspectives drawn from strategy and organization fields.

One of the limitations of this study is that it does not consider the cross-cultural dimension of BA adoption. Thus, the generalizability of the current study is somewhat limited because it was conducted in the

Turkish business environment. Although BA by its nature is context specific due to the variations in analytics industry, replications of the conceptual model in other country settings would improve its generalizability. Moreover, emergent and developed country comparative perspectives need to be researched as well. Second, we tested our research model relying on cross-sectional data, thus we recommend retesting the findings using panel data to examine its stability. A longitudinal study can also be conducted to see the time-dependent differences in BA adoption. Third, in our study we employed perceptual performance indicators, which could be substituted or accompanied by objective indicators to provide a solid picture of the link between BA adoption and firm performance. We should also acknowledge that BA methodology unfortunately lacks an ethical analysis dimension; given the rise of algorithms and their influence on individuals and society, and concerns about data use and privacy, then an ethical analysis stream in BA may constitute a useful area for further research. Finally, we did not examine the roles of BA capabilities, top management commitment and organizational culture in BA adoption, which could be considered as moderating variables to further knowledge in the big data economy.

Appendix A. Measurement of survey-based constructs

Construct	Items	Source(s)
Adoption of business analytics (BA)	Please identify the relative use of the following BA applications in your firm using 5-point scales (ranging from 1 = "never" to 5 = "always").	
BA: Data acquisition and processing (DACQ)	1. Information propagation 2. Data warehousing 3. Data capturing system 4. Document management system	Zwass (1998), Alter (2002), Sharda et al. (2014), Laudon and Laudon (2013), Hindle and Vidgen (2018).
BA: Prescriptive analytics (PRES)	1. Data analysis system 2. Product development system 3. E-commerce	
BA: Predictive analytics (PRED)	1. Marketing intelligence system 2. Investment intelligence system 3. Data mining 4. Decision support system	
BA: Descriptive analytics (DESC)	1. Visualization 2. Scorecard 3. Dashboard 4. OLAP analysis	
Business process performance (BPER)	Please indicate the level of your agreement to the following statements that are related to the effects of BA applications on your firm's business process performance using 5-point scales (1 = "strongly disagree" to 5 = "strongly agree"). 1. Our firm has rapid and effective internal and external coordination for its regional, national and global activities 2. Our firm is successful in gaining economies of scale. 3. The productivity of labor has been improved. 4. Our customers' requests have been adequately responded. 5. Our meetings and discussions have been held efficiently and effectively.	Mahmood and Soon (1991); Elbashir et al. (2008), Bayraktar et al. (2009), Mclaren et al. (2011), Mithas et al. (2011), Luo et al. (2012).
Firm performance (FP)	Please indicate the level of your agreement to the following statements that are related to the effects of BA applications on your firm performance using 5-point scales (1 = "strongly disagree" to 5 = "strongly agree"). 1. Our firm has achieved a high level of return on sales. 2. Our firm's distribution cost has been reduced. 3. Our firm has increased its market share. 4. Our firm has achieved a high level of return on investment. 5. Our firm's administrative expenses have been reduced. 6. Our firm's inventory cost has been reduced. 7. Our staff cost has been reduced. 8. Our firm has achieved a higher level of customer loyalty.	Bharadwaj (2000), Radhika and Hartono (2003), Duhan (2007), Glaister et al. (2008), Ordanini and Rubera (2009), Mithas et al. (2011), Akter et al. (2016), Troilo et al. (2016), Ramanathan et al. (2017).

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