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Business Analytics Adoption and Technological Intensity: An Efficiency Analysis

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Abstract
Despite the overwhelming popularity of business analytics (BA) as an evidence-based decision support mechanism, the impact of its adoption on organizational performance has received scant attention from the research community. This study aims to unfold the adoption efficiencies of BA and its applications by proposing a data envelopment analysis (DEA) methodology to holistically assess the underlying factors with respect to the level of achievement regarding organizational performance, operational performance, and financial performance. Furthermore, the study unveils the firm-level and sectoral-level discrepancies in BA adoption efficiency in different industry settings. Relying on survey data obtained from 204 executives in various industries, this study provides empirical support for the cross-industry differences in BA adoption efficiencies. The results show that the firms in low-tech industries seem to achieve the highest efficiency from adopting BA regarding its influence on firm performance.

Keywords Business analytics · Decision-making performance · Operational performance · Organizational performance · Resource-based view · Data envelopment analysis (DEA) · Emerging countries · Turkey

1 Introduction

Digital transformation and the advancements in information and communication technologies contribute to generating massive amounts of data worldwide. Now, firms strive to generate value from these structured and unstructured propagated data pools. Under the presence of uncertainty, stiff market conditions force the firms continuously reduce their cost, improve their margins and create sustainable growth. According to the 2021 Gartner CEO and senior business executive survey, investors' expectations are shifting to higher profit returns (Lupu, 2021). By building business models and analyzing the collected data, firms seek solutions to improve their performance and create a competitive advantage in the market (Cosic et al., 2015). Therefore, business analytics (BA) tools and techniques are used in every industry sector to handle this massive volume of data pouring into organizations (Ahmad et al., 2022). Industries adopting these applications report tremendous performance success (Huang et al., 2017). The high investment costs of BA applications and technologies make these efforts even more challenging for public and private sector companies. Considering BA's unrealistic and exaggerated expectations,

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there is a rising requirement to assess the effect of its adoption on organizational performance.

The recent Covid-19 pandemic clearly showed the importance of making big decisions quickly and precisely. Even though a tremendous amount of data exists now, Dighe (2021) reports that decisions are poor and managers still need data-driven decision-making to support stakeholders' preferences. The Gartner portfolio decision-making survey lists the five indicators of high-quality decision-making (Dighe, 2021): strategic clarity, assessment rigor, information quality, process quality, and stakeholder coaching. Only one percent of the organizations could fulfill these five indicators (Dighe, 2021). However, high-quality decisions lead to maintaining business continuity, generating value for the business, gaining a competitive advantage, and exceeding business expectations (Kinnunen, 2021). As listed among Gartner's top strategic technology trends for 2023, applied observability, using data in a highly orchestrated and integrated fashion across business functions, is expected to achieve shorter latency for decision-making and enable competitive advantage for most of the target businesses (Groombridge, 2022).

One of the expectations from the digital transformations and BA adoptions is to enhance operational efficiency. Disruptions and the unpredictability of the operating environment are the biggest obstacles to operational performance and make the resilience of supply chains even more mission-critical. Therefore, digitalized operations are one step toward achieving operational excellence and making businesses more transparent, traceable, and adaptable. Learning from past failures and mitigating the potential risks, digital immune systems also help to create resilient supply chains for better customer experience. Wireless technologies provide cost-efficient, reliable, and scalable infrastructures (Groombridge, 2022) for tracing production processes, refreshing inventories, and delivering services.

Of course, the bottom line measure for success in the business world is to create sustainable growth, engendering value from data to yield financial performance. In addition to digitalization efforts, newer technologies such as metaverse, super apps, artificial intelligence, and machine learning introduce new perspectives and challenges to our regular business activities. Access to these untapped market segments through fast, reliable, and efficient delivery of goods and services may grow a firm, reduce processing costs, and increase revenue to enhance its return on investments and market share.

Each industry sector, in practice, has different needs and expectations. Therefore, BA applications should be employed at different capability levels. Many software vendors provide industry-specific solutions to firms and share their industry-specific experiences to promote their products. Specialization of the workforce in each of these application modules is also quite common practice. In various industries, data acquisition and processing, descriptive, predictive, and prescriptive analytics applications may impact organizational performance differently. The adoption levels of different BA tools may vary depending on the firms' technological advancement level. Businesses widely use descriptive analytics tools such as Excel, basic statistical analysis tools, and Google Analytics at all levels of technological advancement. The more advanced ones may use more sophisticated descriptive analytics tools (e.g., Power BI, Hadoop, and Apache Spark) with visualization capabilities while handling larger datasets. Low-technology firms, generally, may lack appropriate IT infrastructure, data, and resources to implement predictive and prescriptive analytics tools. They may rely on their basic tools for limited prediction capability. Firms with higher technological advancement, such as those in the technology or financial industries, commonly use predictive analytics tools such as IBM SPSS, SAS or tools that implement R and Python programming languages. Firms investing significantly in their technological infrastructure typically use more advanced prescriptive analytics tools such as IBM Cognos Analytics, SAP Predictive Analytics, and Alteryx. However, adoption efficiency is concerned with using resources to reach the expected performance levels, which may be related to the applications' maturity, capability, and fitness to achieve a firm's performance metrics. Prior studies have explained the benefit of adopting BA applications from a holistic perspective (Aydiner et al., 2019a; Braganza et al., 2017; Davis & Woratschek, 2015; Wu et al., 2017). However, there is still a need for sectoral analysis of the adoption of BA applications, considering sectoral expectations and differences. This study aims to unfold BA applications' adoption efficiencies and develop a model using data envelopment analysis (DEA) to assess them. DEA is a unique tool to assess the multiple performance indicators for the set of inputs. It represents the overall efficiency with a single value. Secondly, the study unveils the firm-level and sectoral differences in BA adoption efficiencies in different industry sectors to identify the most efficiently adopted BA applications in each industry. Our extensive literature survey did not catch any study exploring the sectoral analysis of the BA tools. Therefore, this study will be one of the first studies in information systems literature exploring sectoral differences using the DEA tool.

The rest of this study is structured as follows. The following section provides a literature review and the study's theoretical background. Then, the research method is presented in detail, followed by the analysis and results. The final section includes the discussion and conclusion, managerial implications, and future research suggestions.

2 Literature Review and Theoretical Background

The capability to renew organizations whenever necessary is a leading strategy for future enterprises (Wójcik, 2015). A firm may develop this capability by learning from past experiences and developing tacit knowledge. BA may play a critical role in reshaping the business and dramatically improving the firm's performance (Ramanathan et al., 2017). Thus, the adoption of BA applications for organizational performance in terms of decision-making performance (DMP), operational performance (OPP), and financial performance (FIP) is discussed in the following subsections.

2.1 Business Analytics

BA includes many technologies and complex implementation processes for big data as a recently emerging field. The complexity begins with collecting massive amounts of structured and unstructured data from various fields (Kohavi et al., 2002). It increases exponentially with the data's variety, velocity, and volume. The backbone of BA is data to execute endpoint analysis. Transforming big data into evidence-based business decisions is a real challenge (Hindle et al., 2020).

Meanwhile, different application domains improve the evolution of BA processes (Duan et al., 2020), providing a rich set of business and technical activities and, in return, building up a data-driven, fact-based management approach (Cosic et al., 2015; Duan et al., 2020). Data-driven and fact-based approaches necessitate the adoption of BA with the collection, storage, retrieval, and analysis of extensive data resources. Thus, BA adoption elevates different categories that derive diverse analytical behaviors and tactics with extensive data collection.

A firm needs to develop its capability regularly to find opportunities to expand its business (Peppard & Ward, 2016). Of the analytical capabilities necessary to deal with sophisticated data processes, BA adoption has several levels. Davenport and Harris (2017) associate these firm capabilities with the four eras of BA. The first one is Analytics 1.0, which emphasizes the historical perspective of data, creating reports and representing them visually through so-called descriptive analytics (DSA). Analytics 2.0 represents the era with a high volume of data analysis characterized by big data processing using various tools. The third era is called Analytics 3.0 and combines structured and unstructured data to create new models for businesses using prescriptive analysis (PSA). Lastly, Analytics 4.0 exemplifies the era of autonomous analytics using artificial intelligence (AI) and cognitive technologies to establish the predictive analytics (PDA) level of BA adoption (Davenport & Harris, 2017). Similarly, as suggested by INFORMS, the functional BA categories considering the different types of tools and techniques employed in BA adoption are classified as descriptive (DSA), prescriptive (PSA), and predictive (PDA) analytics (Aydiner et al., 2019a; Duan et al., 2020; Sharda et al., 2014). Moreover, Aydiner et al., (2019a, 2019b) state that data acquisition and processing (DAP) constitute the first step of the BA adoption levels and establish a distinctive antecedent for analytics technologies (Aydiner et al., 2019b). An organization's capability of implementing BA applications to reshape its resources and practices varies and influences its firm value and competitive advantage (Vidgen et al., 2017). All these levels are somewhat sequential, and it is complicated to progress to the next level without developing adequate capability. The specific abilities to define a level and its associated applications craft the four analytics categories (DAP, DSA, PSA, and PDA) (Aydiner et al., 2019a; Davenport & Harris, 2017; Sharda et al., 2014; Sun et al., 2017).

Despite its importance, there is a paucity of research on DAP for BA adoption (Duan et al., 2020). DAP explores the internal and external business potentials with big data applications such as information propagation, data capturing, data warehousing, and document management systems. DAP is considered the foundation for all the adoption levels to build a BA capability and the first step in building big data to store them and make them available when needed.

Enterprises need to retrieve data regularly and process it to yield information about their business from their activities happening in the past and the present. DSA applications transform the insightful data collected through DAP applications into a form that is more meaningful and easier for decision-makers to understand. The inquisitiveness of the business environment raises many questions about firms' operations (Aydiner et al., 2019b; Duan et al., 2020). DSA applications develop monitoring capabilities for decision-makers, enabling them to benchmark past data to analyze and compare them with new data. This capability invokes an understanding of the current business conditions and enhances operational decisions (Appelbaum et al., 2017; Delen & Zolbanin, 2018; Sharda et al., 2014). Thus, this study considers DSA as the capability to monitor business transactions introduced through IS applications such as data visualization, scorecards, online analytical processing (OLAP), and dashboards (Sivarajah et al., 2017).

In BA adoption, PDA represents a higher level of capability than DSA. PDA applications can enhance the visibility and robustness of data to predict the future using machine learning methods and various statistical models (Aydiner et al., 2019b; Duan et al., 2020; Sharda et al., 2014). The power of PDA applications lies in their ability to convert big data into operational business information and decisions. Through "what-if" analysis, PDA creates simulations that visualize the impact of possible decisions on decision-makers (Kunc and O'brien, 2019). Thus, we characterize PDA as IS applications, such as investment intelligence, market intelligence, data mining, and decision support systems that transform theory into operational results (Shmueli & Koppius, 2011).

Using advanced technologies and mathematical models, such as artificial intelligence, case-based reasoning, and multi-criteria decision-making tools, PSA initiates business value creation and supports strategic decision-making (Duan et al., 2020; Pape, 2015; Sharda et al., 2014). The identification of optimal behaviors and activities and the capability to answer the questions of "now what?" or "what do we do next?" in the development of innovational business solutions with declining strategic decision-making costs create a competitive business environment (Davenport & Harris, 2017; Sivarajah et al., 2017). In our model, product development, data analysis, and e-commerce systems are also parts of PSA.

Accordingly, DAP, DSA, PDA, and PSA applications represent the adoption levels of BA, and their usage influences the organizational performance assessed by DMP, OPP, and FIP.

2.2 Organizational performance

Aligning a firm's BA applications with its business processes and organizational strategies leads to significant performance advances (Ramanathan et al., 2017; Tan et al., 2016). BA improves the quality of the decisions made and the effectiveness of the business processes and increases profitability. Thus, DMP, OPP, and FIP are selected as indicators to appraise organizational performance.

2.2.1 Decision-Making Performance

Timely, accurate, and reliable data are essential for effective decision-making. BA uses these data to predict the future of uncertain and dynamic business environments, seize new business opportunities, and make fast and inclusive decisions (Huber, 1990). Effective decision-making processes increase the organization's intelligence, enhancing communication channels and deploying timely information within the organizational hierarchy. This capability boosts a firm's data-driven culture to actualize strategic plans (Karaboga et al., 2022). Thus, BA adoption expedites quality decision-making and improves firm performance (Baum & Wally, 2003).

2.2.2 Operational Performance

Successful BA applications analyze big data and transform it into invaluable information, helping to understand better customer needs and market behaviors, which are vital in designing successful business operations (Baum & Wally, 2003). Business operations supporting the strategic plans of a firm result in the growth of the firm's market share and increase its customer satisfaction and competitive power (Bisogno et al., 2016; Mithas et al., 2011). Wu et al. (2015) state that OPP denotes the firm's responsiveness to customer needs and expectations, the efficiency of its business processes, and its competitiveness. Popovič et al. (2018) show that big data analytics may augment manufacturing performance. Therefore, BA adoption maintains, analyzes, and advances the OPP of a firm (Sun et al., 2017).

2.2.3 Financial Performance

Many studies, including but not limited to Cosic et al. (2015), Elbashir et al. (2008), Larson and Chang (2016), Ramanathan et al. (2017), and Troilo et al. (2016), state that the adoption of BA has an impact on a firm's financial performance and increases its business value and competitive advantage. High-quality, relevant, accurate, and timely data to manage a firm's daily processes and derive strategic initiatives are a critical resource and an invaluable asset that significantly affects financial performance (Appelbaum et al., 2017). BA applications in a firm pave the way to actualizing its strategic objectives and equipping its business processes to achieve better customer satisfaction (Holsapple et al., 2014). By encouraging a collaborative business environment and knowledge sharing, BA adoption increases creativity and competitive advantages, leading to significant financial performance (Klatt et al., 2011).

2.3 BA and Technological Intensity

BA applications are mainly designed to understand the market and improve organizational performance. Big data analytics help to identify the different market segments and serve them individually to create an unprecedented customer experience in many industries. This growing interest in big data and BA also encourages research on various practical issues (Huang et al., 2017). One of these issues arises from the differences in the expectations of industries with various technological intensities for adopting BA applications. Performance disparities among these industries for adopting BA applications is a worthwhile research topic, considering the efforts and money invested into these applications. Therefore, it is crucial to identify the specific industrial contexts and their necessities regarding BA applications (Troilo et al., 2016). For instance, the financial industry receives real-time information, engages in real-time decision-making, and needs real-time customer tracking. The healthcare industry tries to cut costs and facilitate high-quality services. The retail industry uses information to improve the working environment along with customer satisfaction (Ji-fan Ren et al., 2017). Numerous industry expectations guide BA users to combine different technologies throughout organizations. Hence, the stage of business domains, organizational vision, and industrial knowledge shape the skill set required for BA applications and the adoption level of the BA (Cosic et al., 2015). Besides, the acquisition and processing of data require regulatory obedience in every industry. Regulation controls and restricts data usage. Thus, investigating the relationships between BA applications and industry sectors will shed light on the adequacy and level of BA adoption to enhance organizational performance. Therefore, resource heterogeneity of data and different levels of BA applications may influence the decision-making and organizational performance in various industry sectors (Akter et al., 2016).

3 Research Methods

3.1 The Survey Context and Data Collection Procedure

The data was collected from Turkey, displaying similar characteristics to the other emerging countries regarding the structure of information and communication technologies (ICT). The ICT market size of Turkey was \$29.9 billion in 2021, representing a 7% growth compared to the previous year (Deloitte Turkey, 2022). The share of information technologies also grows faster within the ICT market. Nearly 185,000 people were employed in the ICT industries as of 2021. Turkish firms are open and willing to digital transformation but lack the necessary ICT infrastructure and qualifications (Izmen et al., 2021). The main barriers to developing the Turkish ICT industry further are the shortage of qualified workforce, lack of clear vision, and the cost of using ICT, similar to many emerging countries.

The survey instrument used in this study was developed according to the procedures suggested in previous research (Dillman, 2007). The questionnaire constructs were adopted from the extant literature (Bayraktar et al., 2009; Hindle & Vidgen, 2018; Laudon & Laudon, 2013; Ramanathan et al., 2017; Sharda et al., 2014) to assess the BA adoption levels (namely DAP, DSA, PSA, and PDA) and the organizational performance indicators (namely DMP, OPP, and FIP). For the content validity of the constructs, the procedure advocated by Hair et al. (2007) was used. Initially, three chief technology officers (CTOs) were interviewed about their views on emerging issues in BA in Turkey. Later, the initial survey questionnaire was modified, considering the views of several expert academics, and finalized with a pre-test performed by six business professionals.

To ensure the presence of BA tools and the usage of their applications, medium, and large-sized firms from several product-intensive industries in Turkey were targeted. A random sample of 800 firms was selected from the Union of Chambers and Commodity Exchanges database of Turkey (TOBB). The TOBB is Turkey's largest non-profit, non-governmental organization, with 365 Chambers and Commodity Exchanges. The responses were gathered using a cross-sectional mail survey instrument. The senior managers or medium-level managers who were knowledgeable about the entire firm's operations were asked to complete the questionnaire. Those who failed to meet these criteria were removed during the data analysis process. Of the 235 questionnaires returned, 204 were usable, with a 20.4 percent effective response rate. The potential of non-response bias was tested, and no support was found. The possibility of non-response bias was checked by comparing the survey results of the early respondents with late respondents who needed a reminder or a longer time to respond to the survey (Armstrong & Overton, 1977). Using a t-test, we first compared the responses from early and late respondents to our survey and did not find any statistically significant differences ($p > 0.05$). Second, we compared a randomly selected group of 100 non-respondent firms with 204 respondent firms. Again, we did not find significant differences for organizational level indicators (e.g., annual sales, years of operation, and the number of employees). Hence, no evidence was found for non-response bias. Table 1 summarizes the key characteristics of the sample.

3.2 Operationalization of the Constructs

This study classified seven constructs into two categories, namely *the adoption of BA* and *organizational performance*, to denote the research model's inputs and outputs, respectively. Considering the nature of the research questions and the study context, the constructs were assessed using five-point Likert scales. In the extant literature, it is common to see studies using as few as five and as many as nine-point Likert scales (Cox, 1980). Though a 7-point Likert scale may offer more nuance and detail in respondents' answers, a five-point scale is simpler and easier for participants to understand and less time-consuming to complete. Therefore, it helps to increase the response rate and quality (Babakus & Mangold, 1992; Devlin et al., 1993). It is worthwhile to point out some studies using a five-point scale from recent information systems literature (e.g., Attili et al., 2022; Bandara et al., 2023; Chatterjee et al., 2022; Gupta et al., 2019).

The adoption of BA was measured using four constructs: DAP, PSA, PDA, and DSA. These constructs were adapted from the literature related to BA and IS (Hindle & Vidgen,

Table 1 Characteristics of the sample

Characteristics			Number		%
Respondent position		Senior/executive manager	106		52
		Middle/first-line manager	98		48
Number of employees		Less than 250	93		46
		251–500	24		12
		501–1000	21		10
		1001–5000	42		20
		More than 5000	24		12
Years of operation		Less than 5 years	8		4
		5–10	26		13
		11–30	107		52
		31–50	33		16
		More than 50	30		15
Annual revenue (Turkish Lira in million)		Less than 25	34		17
		25–99	44		21
		100–249	26		13
		250–499	19		9
		Equal or more than 500	81		40
Industry sectors	*High-tech industries: (R&D intensity ≥ 5%)*	IT and other information systems	23	75	37
		Electrical equipment and machinery	15		
		Chemical and pharmaceuticals	9		
		Computer and consumer electronics	11		
		Motor vehicles and other transport equipment	17		
	Medium-tech industries: (R&D intensity ≥ 0.5%, but < 5%)	Food products and beverages	16	58	28
		Textile, apparel, and leather	26		
		Petroleum, tire, and plastics	8		
		Paper, wood, and furniture	5		
		Other non-metallic mineral products	3		
	Low-tech industries: (R&D intensity < 0.5%)	Financial services	14	71	35
		Construction and real estate activities	11		
		Human health and social work activities	16		
		Wholesale and retail trade	30		
TOTAL:			*204*		

2018; Laudon & Laudon, 2013; Sharda et al., 2014; Zwass, 1998).

DMP, *OPP*, and *FIP* were assessed as indicators of organizational performance. *DMP* appraises the effectiveness of a firm's decision-making. The survey items for this construct were identified from the prior literature (Aydiner et al., 2019a; Bayraktar et al., 2009; Gable and Poore, 2008; Huber, 1990; Luo et al., 2012; Mahmood & Soon, 1991; McLaren et al., 2011; Mithas et al., 2011; Tippins & Sohi, 2003). The OPP items were drawn from previous studies (Aydiner et al., 2019a; Bayraktar et al., 2009; Elbashir et al., 2008; Luo et al., 2012; Mahmood & Soon, 1991; Mclaren et al., 2011; Mithas et al., 2011). Assessing *FIP* is consistently found to be quite challenging in the extant literature. Previous studies have adopted either a subjective or an objective approach to measuring financial performance. Based on managers' perceptions of performance, the subjective approach has been used extensively in empirical studies. Several writers have also justified this approach (e.g., Collings et al., 2010; Geringer & Hebert, 1991; Venkatraman and Ramanujam, 1986) , and all noted consistency between managers' perceptions of performance and objective measures. Therefore, *FIP* was gathered from earlier studies measuring the BA and IS (Akter et al., 2016; Aydiner et al., 2019a; Bharadwaj, 2000; Duhan, 2007; Glaister et al., 2008; Ordanini & Rubera, 2009; Radhika & Hartono, 2003; Ramanathan et al., 2017; Troilo et al., 2016).

Based on R&D intensity, Galindo-Rueda and Verger (2016) updated the OECD taxonomy of the international standard industrial classification. R&D intensity is the proportion of R&D expenditures to the gross output or gross value added (Carroll et al., 2000; Galindo-Rueda & Verger, 2016). In this study, R&D intensity indicates the technological intensity of the industry sectors. Regarding R&D intensity, three main categories representing industry-specific characteristics were identified: high-tech, medium-tech, and low-tech industries. Consistent with Carroll et al. (2000) and Galindo-Rueda and Verger (2016), industries with an R&D intensity of 5 percent and more were classified as high-tech. If the R&D intensity was less than 5 percent but more than 0.5 percent, these industries were called medium-tech industries, whereas the rest were labeled low-tech industries. Following this definition, the specific industries covered in this study are listed in Table 1.

The study's constructs and their sources are presented in the Appendix.

3.3 Data Envelopment Analysis Model

As a mathematical programming approach, data envelopment analysis (DEA) measures the relative efficiency of similar decision-making units (DMUs) (Cook & Zhu, 2005; Cooper et al., 2000). As a linear model, it is similar to regression models measuring only the average functional relationship between inputs and a single output. However, the DEA is a more relevant and widely used tool to assess the performance of a unit with multiple outputs based on a given set of inputs and represent the overall performance with a single score (Bayraktar et al., 2012, 2013; Cook, 2004; Demirbag et al., 2010; Forker & Mendez, 2001; Korpela et al., 2007; Liu & Wang, 2008; Sarrico & Dyson, 2000; Zhu, 2003). With DEA, it is easy to compare DMUs while identifying the potential improvement possibilities for each inefficient DMU. DEA is flexible to allow building models as each input and output variable can be defined in different measurement units. Efficient DMUs construct the efficiency frontier and envelop the non-efficient ones. Therefore, there is no need for any assumption about the form of the production function and a priori knowledge about the weights of variables (Cooper et al., 2000). DEA benchmarks the inefficient DMU with a convex combination of the efficient ones and indicates the sources of inefficiencies.

For m outputs, n inputs, and k DMUs, an output-oriented DEA model developed by Charnes et al. (1978) is formulated below:

$$Max\ \ \phi_o + \varepsilon\Big(\sum_{i=1}^{n} e_{io} + \sum_{j=1}^{m} d_{jo}\Big) \tag{1}$$

Subject to

$$\sum_{r=1}^{k} \lambda_r x_{ir} + e_{io} = x_{io}\ \ i = 1, \ldots, n \tag{2}$$

$$\sum_{r=1}^{k} \lambda_r y_{jr} - d_{jo} = \phi_o y_{jo}\ \ j = 1, 2, \ldots, m \tag{3}$$

$$e_{io}, d_{jo}, \lambda_r \geq 0\ \ For\ all\ i,\ j,\ r \tag{4}$$

where;

o	The firm (DMU) under efficiency evaluation for the adoption level of BA applications
φ_o	The BA adoption efficiency score of the firm (DMU) o
x_{io}	The adoption level of BA application (input) i for the firm (DMU) o
y_{jo}	The level of organizational performance indicator (output) j for the firm (DMU) o.
e_{io}	The amount of excess adoption in BA application (input) i for the firm (DMU) o.
d_{jo}	The amount of deficit in organizational performance indicator (output) j for the firm (DMU) o
$\varepsilon>0$	A predefined non-Archimedean element
λ_r	The dual variable used to construct a hypothetical composite firm to dominate firm o under evaluation
m	The number of organizational performance indicators (outputs) considered
n	The number of BA applications (inputs) considered
k	The number of firms (DMUs)

The objective function (1) ensures that firm o may get the maximum possible efficiency score (φ_o) relative to the others under consideration. If firm o is efficient ($\varphi_o = 1$), all the slacks (output deficits and input excesses) are expected to be zero for total efficiency. Constraint (2) ensures that the hypothetical composite adoption level of BA application i for firm o is a linear combination of the adoption levels of each firm and the excess input of i. Similarly, constraint (3) states the same condition for the hypothetical composite performance indicator of j for firm o. In the optimal solution of the model (1–4), firm o is efficient if $\varphi_o = 1$ and $e_{io} = d_{jo} = 0$ for all input i and output j (Cooper et al., 2000).

The model (1–4) above is a typical output-oriented CCR–DEA model emphasizing constant returns to scale (CRS), referring to the exact proportional change in the outputs and inputs (Cook & Zhu, 2005). Keeping the current level of inputs, the model (1–4) exploits the efficiency of the DMU and benchmarks it with the efficient ones (Cooper et al., 2000). The model can be extended to variable returns to scale (VRS) by adding the constraint $\Sigma\ \lambda_r = 1$ (Banker et al., 1984).

4 Analysis and Results

This study assesses the efficiency with which firms adopt BA applications to achieve enhanced organizational performance through an output-oriented BCC model. The discrimination problem in DEA may arise when the number

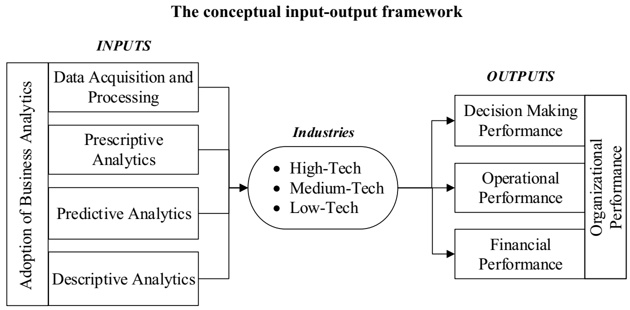

Fig. 1 The conceptual input–output framework

of variables is relatively large compared with the number of DMUs. To reduce the number of variables in DEA with the minimum loss of information (Adler & Golany, 2002), we used multi-attribute constructs comprising four inputs (n) and three outputs (m). Therefore, the reliability analysis and convergent and discriminant validity for each construct were tested. Cooper et al. (2000) suggest having at least as many DMUs as the maximum of m*n and 2(m + n) for such a study. With four inputs (n) and three outputs (m), our 204 firm responses acting as DMUs are sufficiently large and satisfy the above condition. The framework of the DEA model to compute the efficiency of each DMU is displayed in Fig. 1.

4.1 Reliability and Validity

Cronbach's alpha values were calculated to measure the reliability of each construct in the model. Our study assessed BA adoption levels through four constructs: DAP, DSA, PDA, and PSA. Their Cronbach's alpha values were 0.80, 0.88, 0.86, and 0.60, respectively. The Cronbach's alpha reliability for the DMP, OPP, and FIP constructs was 0.85, 0.77, and 0.81, respectively. The results presented in Table 2 indicate that the constructs are unidimensional, and their reliability metrics exceed the desired/required levels (Hair et al., 2007; Nunnally, 1978; Tenenhaus et al., 2005).

The composite reliability (CR) factors assessing the internal consistency of the constructs are provided in Table 2. The CR values are consistent with the threshold value of 0.70 (Fornell & Larcker, 1981), and the constructs used in the study are reliable. The average variance extracted (AVE) estimates are also presented in Table 2. The values satisfy the threshold value of 0.5 (Fornell & Larcker, 1981). Therefore, the study's constructs endorse convergent validity and scale reliability.

Nine pairwise tests were conducted to gauge how different the constructs were. Their results support the discriminant validity of each pair, as shown in Table 3.

Table 2 Unidimensionality of the constructs

Construct	Number of items	AVE[a]	CR[b]	Cronbach's Alpha
Data acquisition and processing (DAP)	4	0.50	0.80	0.80
Descriptive analytics (DSA)	4	0.62	0.87	0.88
Predictive analytics (PDA)	4	0.57	0.84	0.86
Prescriptive analytics (PSA)	3	0.50	0.75	0.60
Decision-making performance (DMP)	6	0.51	0.86	0.85
Operational performance (OPP)	5	0.50	0.83	0.77
Financial performance (FIP)	8	0.52	0.89	0.81

[a]Average variance extracted

[b]Composite reliability

Table 3 Discriminant validity of the constructs

Test #	Description	χ^2 model	χ^2 unconstrained model	Difference*
1	DSA→PDA	15.55	11.65	3.90
2	DSA→PSA	17.79	11.97	5.82
3	DSA→DAP	43.59	37.43	6.16
4	PDA→PSA	34.49	19.73	14.76
5	PDA→DAP	43.48	25.64	17.84
6	PSA→DAP	40.18	24.27	15.91
7	DMP→ OPP	152.28	66.91	85.37
8	DMP →FIP	259.80	158.57	101.23
9	OPP →FIP	241.57	167.85	73.72

*All values are significant at $p < 0.01$

4.2 Descriptive Analysis

The descriptive statistics of the constructs are shown in Table 4. The F-test results show no statistically significant differences among the industry sectors regarding the adoption level of BA applications and the organizational performance indicators. However, pairwise comparisons of the adoption levels of different BA applications within the same industry show some statistically significant differences in Table 4. DAP and PSA are adopted much more than DSA and PDA in all the industry types, while PDA is the least-utilized BA application. In low-tech and high-tech industries, DAP's adoption level is significantly higher than that of PSA. Surprisingly, PDA was adopted less than any other BA application in an emerging country like Turkey.

4.3 Efficiency Scores of the Firms

Based on the input and output variables, as shown in Fig. 1, a DEA model was developed to measure the efficiency of adopting BA applications in terms of the level of achievement for

Table 4 Descriptive statistics for the adoption level of BA applications and their impacts on performance indicators

	Industries								F-test[†]
	Medium-tech		High-tech		Low-tech		Total		
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	
BA Adoption (Inputs)									
Data acquisition and processing (DAP)	3.61	0.97	3.83	0.94	3.82	0.82	3.77	0.91	1.165
Descriptive analytics (DSA)	2.92	0.98	3.26	1.05	3.16	1.19	3.13	1.08	1.672
Predictive analytics (PDA)	2.88	1.11	3.18	0.98	3.10	1.04	3.07	1.04	1.424
Prescriptive analytics (PSA)	3.47	1.03	3.45	0.95	3.36	0.95	3.42	0.97	0.259
Organizational performance (Outputs)									
Decision-making performance	3.67	0.68	3.71	0.60	3.83	0.56	3.74	0.61	1.256
Operational performance	3.95	0.62	4.04	0.54	3.99	0.56	4.00	0.57	0.465
Financial performance	3.62	0.63	3.61	0.49	3.66	0.58	3.63	0.56	0.148
Pairwise comparisons	t-values								
DAP—DSA	9.14**		6.85**		6.22**		12.12**		
DAP—PDA	7.77**		8.01**		7.91**		13.69**		
DAP—PSA	1.53		3.85**		4.54**		5.92**		
DSA—PDA	0.40		1.03		0.68		1.224		
DSA—PSA	-4.76**		-1.89		-1.83		-4.70**		
PDA—PSA	-5.39**		-2.83**		-2.64*		-6.10**		
Total number of firms	58		75		71		204		

[†]All of the F values are insignificant

*$p < 0.05$; **$p < 0.01$

S.D. = Standard deviation

Table 5 Kruskal–Wallis rank test results for output-oriented BCC DEA efficiencies

Assumption	*Industry types*	Efficiency scores		KW	p-value
		Mean	SD		
No-difference among the sectors	Medium-tech industries	0.876	0.097	0.487	0.784
	High-tech industries	0.873	0.094		
	Low-tech industries	0.885	0.094		
	Total	0.878	0.094		
Some differences among the sectors	Medium-tech industries	0.987	0.045	16.606	0.000
	High-tech industries	0.997	0.048		
	Low-tech industries	1.002	0.050		

organizational performance. DAP, DSA, PDA, and PSA represent the BA applications adopted by the firms and are called inputs in DEA terminology. Similarly, DMP, OPP, and FIP are the indicators of organizational performance, and they are the outputs of the DEA model. Using the output-oriented super-efficiency BCC–DEA model, the firms in the sample are benchmarked against each other by assessing their efficiencies in adopting BA applications. As shown in the first part of Table 5, the industry sector averages of the firm efficiencies are assessed as 0.876, 0.873, and 0.885 for the medium-tech, high-tech, and low-tech industry sectors, respectively. Similar to the results of the descriptive analysis, the sector efficiencies do not vary much among different industries (KW = 0.487, $p < 0.784$). However, this analysis assumes no structural difference among the various industries adopting BA applications. In practice, it is a pretty well-known fact that every industry has its own needs and specifications when the time comes to implement information systems successfully. The following section will evaluate the assumption that no structural difference exists among industry sectors.

4.4 Comparison of Sectoral Differences Among the Different Industries

Regarding the efficiency analysis of adopting BA applications, two potential sources of inefficiencies are possible for the firms: industry-specific and firm-specific inefficiencies.

Table 6 Rank sum test results for pairwise comparisons

Comparison of industry sectors				KW
Industry 1	Mean rank†	Industry 2	Mean rank†	
Low-tech industries	122.17	Medium-tech industries	79.63	4.071**
Low-tech industries	122.17	High-tech industries	101.57	2.126*
High-tech industries	101.57	Medium-tech industries	79.63	2.127*

†Rank represents the place of a firm in an increasing order list of efficiency scores

*$p<0.1$; **$p<0.01$

Table 7 The source of sectoral inefficiencies

		Average improvement potential of industries (%)			F-test
		Medium-tech industries	High-tech industries	Low-tech industries	
Input excesses	Data acquisition and processing	3.31**	2.32**	7.33**	7.378**
	Descriptive analytics	5.37**	3.71**	2.65*	1.165
	Predictive analytics	2.42*	5.93**	4.37**	2.078
	Prescriptive analytics	5.26**	2.52**	3.17*	1.135
Output deficits	Decision-making performance	3.54	3.22**	0.90*	3.603*
	Operational performance	1.10*	0.43	1.43*	0.627
	Financial performance	0.51**	1.03*	1.79**	1.634

*$p<0.05$; **$p<0.01$

Industry-specific structural differences affect all the firms within the sector, and it would not be fair to benchmark these firms against those belonging to other industries. Several studies in the extant literature suggested a methodology to examine the industry-specific variations. Brockett and Golany (1996) proposed a procedure to check efficiency differences in DEA with only two categorically inherent sectors. Sueyoshi and Aoki (2001) extended this earlier study to many categories. The four-step procedure was applied to the dataset in line with both studies to eliminate firm-specific managerial inefficiencies. As a first step to eradicate firm-specific performance issues, the firms are clustered according to each industry sector and assessed their efficiencies within their industry. Later, the inefficient firms in each industry sector are projected into their efficiency frontier. In the third step, a new DEA model (output-oriented, BCC, super-efficiency DEA) is built and populated with all the firms from all the industries with their newly adjusted datasets. This new model of efficiency addresses only sectoral inefficiencies. Lastly, the firms are classified according to their respective industries, and their industry-specific efficiency scores are compared using the Kruskal–Wallis rank test (Sueyoshi & Aoki, 2001).

The final stage of this procedure is presented in Table 5 under sectoral differences. The Kruskal–Wallis rank test results in this table show some discrepancies between the firm efficiencies based on the industry sectors ($p<0.01$). According to rank-sum tests, the pairwise comparisons displayed in Table 6 indicate that the efficiency difference between low-tech and medium-tech industries is the most statistically significant ($p<0.01$). The other pairwise differences are partially significant ($p<0.1$). Therefore, it is possible to comment that low-tech industries, followed by high-tech industries, adopt BA applications more efficiently than medium-tech industries to achieve improved organizational performance.

To investigate the sources of the sectoral differences, the technical inefficiencies, namely input excesses, and the output deficits of the industries, in the standard DEA terminology, need to be evaluated. The average slacks for the input and output variables for each industry sector are presented in Table 7. The significance of each slack in each industry sector was verified through a t-test, and the percentage differences are revealed in Table 7. All the input excesses in each industry are statistically significant. The BA applications are adopted excessively by up to 7.33 percent in every industry. Therefore, BA applications fall short of fulfilling the expectations regarding organizational performance enhancements. DMP has the most statistically significant deficit (3.22 percent) for high-tech industries. The firms in this industry suffer from poor DMP despite their adoption level of BA applications. Both medium-tech and low-tech industries have statistically significant but relatively not very large deficits (0.51 and 1.79 percent, respectively) according to the financial performance indicators.

Among the different industry sectors in Table 7, only two sources of inefficiencies show statistically significant

Table 8 Post-hoc multiple comparisons of significant sectoral differences

	Multiple pairwise comparisons for industries[ξ]		
	Low-tech vs. High-tech	Low-tech vs. Medium-tech	Medium-tech vs. High-tech
Data acquisition and processing (Excess)	0.175**	0.140*	0.035
Decision-making performance (Deficit)	-0.100*	-0.114*	0.014

[ξ]: Dunnett's T3 and Games-Howell tests are used under the not-equal variance assumption

*$p<0.05$; **$p<0.01$

differences according to the F-test results: DAP as input excess and DMP as output deficit. Multiple pairwise sector comparisons are conducted to identify industry-specific characteristics, and the results of these post hoc tests are shown in Table 8. The most significant difference in DAP excesses is between low-tech and high-tech industries. The difference between low-tech and medium-tech industries is also noteworthy.

Regarding the adoption level of DAP, low-tech industries are significantly different from the other two sectors (see Table 8) in such a way that the firms in this industry fail to achieve the expected organizational performance based on their DAP adoption efforts. This result indicates that data are collected but not analyzed thoroughly in low-tech industries. It also explains why data cannot create business value for these industries. Among the performance indicators, only DMP has weak deficit differences between low-tech and high-tech industries as well as between low-tech and medium-tech industries. Firms in low-tech industries are positively discriminated from the other industries since their DMP deficit is slightly smaller than the others, with a significance level of 0.05. These findings may allow us to conclude that firms in low-tech sectors may need to search for ways to fully utilize their potential in BA applications to achieve better organizational performance.

4.5 Comparison of Firm-Level Differences Within the Industry Sectors

Table 9 shows the firm-level inefficiencies in each industry sector and identifies potential improvement directions. The results indicate that excessive adoption of BA applications is statistically significant in every industry ($p<0.01$). Based on firms' current adoption levels, it ranges between 3.31 and 15.12 percent. These excessive efforts, unfortunately, have no impact on organizational performance. This clearly indicates that every industry's BA capability is different, and it is not enough to extract the business value from data. DSA and PSA show the two biggest excesses among the BA adoptions in low-tech industries.

Similarly, PDA and PSA are the top excesses for medium-tech and high-tech industries, respectively. The managers of the firms in these industries consider how these BA applications would help them to enhance organizational performance before implementing them. They should also improve their BA capabilities to acquire the necessary information from the data.

The largest deficits among the organizational performance indicators are related to DMP in each industry. The OPP and FIP are relatively low levels of deficits, indicating that managers should focus more on the decision-making capabilities of BA applications instead of concentrating on passive reporting activities. The firms in high-tech industries have low but statistically significant deficits in OPP and FIP. The managers of high-tech industries should closely follow up all three performance indicators, whereas DMP and OPP are the leading performance indicators for medium-tech industries.

5 Conclusion and Implications

Despite the popularity of BA applications, their impact on organizational performance is subject to substantial discussion. It is difficult to assess the value of BA for a firm and its contribution to creating a competitive advantage. The

Table 9 The source of firm-level inefficiencies

		Average improvement potential of industries (%)		
		Medium-tech	High-tech	Low-tech
Input excesses	Data acquisition and processing	4.95**	10.25**	6.24**
	Descriptive analytics	5.10**	5.52**	15.12**
	Predictive analytics	13.41**	7.47**	6.25**
	Prescriptive analytics	3.31**	14.15**	14.95**
Output deficits	Decision-making performance	3.08**	5.05**	3.55**
	Operational performance	1.15**	0.63**	0.53*
	Financial performance	1.35*	2.65 **	2.25*

*$p<0.05$; **$p<0.01$

multidimensionality of organizational performance also makes comparison quite complex. Each industry sector has specific needs and different adoption levels of BA applications. In this study, a DEA model was developed to assess the adoption efficiencies of BA applications to enhance organizational performance. The adoption of BA applications was evaluated through four constructs, namely DAP, PSA, PDA, and DSA, and considered inputs to the DEA model. Similarly, organizational performance as the output of the DEA was constructed using three performance indicators, DMP, OPP, and FIP. Relying on the data obtained from 204 medium- to high-level managers in various industries in Turkey, this study identified the industry-level and cross-sectoral differences in BA applications and their impact on organizational performances.

According to the descriptive analysis of our data, there are no statistically significant differences in cross-industry-sector comparisons in terms of the adoption level of BA applications and organizational performance indicators. However, DAP and PSA in all industry types are adopted much more than DSA and PDA, while PDA is the least-adopted BA application. This result is surprising for emerging country firms striving to predict the future. We believe that this is related to the nature of emerging countries where political, social, and economic instabilities are quite common characteristics. While predictability is crucial for these country firms, making the right predictions is equally difficult. The lack of good-quality historical data is another shortcoming facing emerging country firms. Considering the complexity of the PDA tools and techniques such as statistics, machine learning, and deep learning, along with the lack of human resource capability, makes adopting PDA applications very challenging for emerging country firms. On the other side, the tools and techniques used for PDA need to be more sophisticated to deal with instabilities such as the ones faced by emerging country firms. However, PSA applications focus on optimizing the decisions, and most of the time, their outcomes on the performance indicators are much clearer and easier to assess.

Our analysis also provides statistical support for the cross-industry differences in BA adoption efficiencies. Low-tech industries, followed by high-tech ones, adopt BA applications more efficiently than medium-tech industries to achieve improved organizational performance. However, the only statistically significant difference in adopting BA applications among the industry sectors belongs to DAP excess. Regarding the adoption levels of DAP, low-tech industries are substantially different from the other two sectors (7.33 percent) in such a way that the firms in this industry fail to achieve the expected organizational performance based on their adoption efforts of DAP. Data collected through DAP in low-tech industries do not generate the anticipated business value. Many reasons are leading to this deficiency in efficiency related to the characteristics of low-tech industries. One is the lack of expertise in integrating DAP with other analytics tools. Data itself does not lead to performance but needs to be transformed into useful forms. A workforce without the necessary data literacy skills to interpret and use it effectively does not make data-driven decisions leading to performance improvements. A lack of data-driven culture in low-tech industries prevents them from understanding the potential benefits of DAP tools. Some of the low-tech industries may have an even more traditional mindset to resist adopting new technologies and processes. In some cases, the processes used by low-tech industries may be so inefficient that no significant improvements in performance may be achieved. Data provide insights about the inefficiencies, but without process optimization, the data may not lead to performance. It should also be noted that storing the data without extracting business value may create a financial burden for low-tech-sector firms that may need to identify ways to utilize their potential for BA applications fully to improve their organizational performance.

Among the organizational performance indicators, the only partly significant ($p < 0.05$) difference within the industry sectors is DMP for output deficit. DMP for high-tech industries has the most statistically significant deficit level (3.22 percent), indicating inadequate DMP compared to the adoption level of BA tools. Surprisingly, the DMP deficit for low-tech industries is the lowest. Relatively poor DMP of high-tech industries may be explained by the complexity of their market conditions and rapidly changing environments, where decisions need to be revised or updated frequently based on new technology, market trends, or other factors. High-tech industries are often under pressure to innovate and develop new products and technologies quickly. This pressure also makes decisions prioritizing short-term gains over long-term sustainability and growth. The need for specialized knowledge and expertise in high-tech industries makes decision-making challenging. The lack of the necessary domain expertise to make informed decisions may lead to poor decision-making that fails to consider all relevant factors. To improve DMP, high-tech industries need to balance data-driven insights and human judgment and take a long-term perspective that considers the impact of decisions on all stakeholders.

5.1 Managerial Implications

In terms of industry-specific firm-level inefficiencies, excessive adoption of BA applications in each industry is widespread, ranging between 3.31 and 15.12 percent based on their current adoption levels. DSA and PSA applications are the largest input excesses among the BA adoptions for the firms compared to their peer industry leaders in low-tech industries. There are several reasons for these excessive adoptions. In general, information system managers and executives working in low-tech industries suffer from a lack of clear strategy and vision for utilizing DSA and PSA tools to reach their overall business goals. They may not have a deep understanding of the capabilities and limitations of these tools. DSA and PSA applications require skilled professionals to operate and interpret the data. However, senior managers and executives in low-tech industries, most of the time, undermine the difficulty and importance of consistently finding and retaining employees with the necessary expertise. These altogether result in poor decision-making.

PSA and DAP are the greatest excesses of high-tech industries. Firms in these industries are often characterized by generating vast amounts of data, being competitive and innovative, and being staffed with technological expertise. Therefore, the senior managers of such firms invest more in tools to manage and analyze their data effectively and to make data-driven real-time decisions quickly. By adopting DAP and PSA applications, firms in high-tech industries may demonstrate their commitment to cutting-edge technology. Therefore, adopting these BA tools is seen as a key part of innovation and staying ahead of the competition for the firms. High-tech industries get benefit from adopting DAP and PSA tools. However, the senior managers and executives of these firms should ensure to balance their need for data-driven decision-making with other essential factors such as intuition and human judgment. They should avoid overemphasizing short-term gains and have the necessary expertise to operate and interpret the data.

Among the medium-tech industry firms, the highest excessive adoption is for PDA. In general, medium-tech firms with tight margins and huge volumes need efficiency to respond to the intense competition. Prediction power is quite essential for these firms. However, enhancing organizational performance through adopting PDA applications depends on many other factors, such as the availability of quality data, human intuition and expertise, and uncertainty in market conditions. Therefore, the managers should know how to align the PDA adoption decisions with the enablers of these technologies to fulfill the organizational performance expectations. It should be noted that the executives involving BA tools should be well aware that investing in human resource capabilities is essential to increase the benefits of BA applications.

Throughout all industry groups, the largest output deficit among the organizational performance indicators is related to DMP. This is a clear indicator that managers at all levels do not take advantage of the decision-making capabilities of BA applications. Data-driven decision-making culture is not a practice followed by industries. Instead, intuition, judgment, and experience are pretty common practices among managers. Therefore, executives and senior managers should utilize BA tools efficiently so that they may catch their peers in their industries.

5.2 Limitations and Future Research

As in most studies, this study has some limitations that should be acknowledged when interpreting the results but also provides avenues for further research. One of the limitations of this study lies in its use of the perceptual measurement of performance constructs, which to some extent, maybe a problematic issue in such studies as ours. It should be noted that quantifying a BA application's impact on a firm's overall performance is challenging, in addition to the time lag between adoption and its possible impacts on the performance indicators.

Although it is difficult to find and develop objective measures, researchers in the field of information systems should be encouraged to supplement subjective data with more objective ones whenever possible. As a further research area, using quantitative data instead of perceptual one may promise a more precise analysis to explore the efficiency differences of the BA adoption in different technological advancements. However, in the absence of quantitative industrial data for analysis, perceptional data collected through the surveys are invaluable despite their well-known potential biases. Another limitation is a relatively small sample size (n = 204) with a low response rate (20.5 percent). Nowadays, achieving high response rates is difficult, specifically in the technological fields involving experts, senior managers, and executives asking for their precious time to complete a survey.

Data for the analysis are collected from a single country. Turkey is one of the emerging countries, but the study's findings may not be generalized to all emerging countries. Cultural, political, and geographical differences among emerging countries may lead firms in different technological advancement levels to act differently in adopting BA applications.

In this study, the adoption of BA applications is considered from the technological advancement levels of the firms. However, as a further research interest, a similar comparison may be performed from many different viewpoints, such as human resource capability, IT infrastructure, IT governance, and top management commitment. Considering the long-term effect of BA on performance, a longitudinal study on the relationship between BA adoption and organizational performance may be a valuable future research direction. Such a study may track the adoption of BA applications over an extended period while measuring organizational performance, potentially providing insights into the long-term benefits or drawbacks of using BA applications in a firm. By better understanding these effects, firms may make more informed decisions about using BA applications to maximize their benefits while minimizing potential drawbacks. The relationship between ethics in BA applications and organizational performance is complex and requires further research. While ethics is crucial in ensuring BA applications are used responsibly and beneficially, unethical use may damage the reputation and reduce organizational performance. One potential area for research may be exploring the ethical challenges and considerations in adopting BA applications in different industries and organizational contexts.

Appendix

Table 10 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 (DAP)	1. Information Propagation 2. Data Warehousing	1. Data Capturing System 2. Document Management System	Zwass (1998), Sharda et al. (2014), Laudon and Laudon (2013), Hindle and Vidgen (2018)
BA: Prescriptive analytics (PSA)	1. Data Analysis System 2. Product Development System	3. E- Commerce	
BA: Predictive analytics (PDA)	1. Marketing Intelligence System 2. Investment Intelligence System	3. Data Mining 4. Decision Support System	
BA: Descriptive analytics (DSA)	1. Visualization 2. Scorecard	3. Dashboard 4. OLAP Analysis	
Decision-making performance (DMP)	*Please indicate the level of your agreement to the following statements that are related to the effects of BA applications on your firm's decision-making performance using 5-point scales (1 = "strongly disagree" to 5 = "strongly agree")* 1. Our company communicates the results of the organizational level analysis to work group and/or functional level operations to enable effective support for decision-making 2. Our company has a culture of facilitating long-term strategic planning 3. Our company makes strategic decisions effectively 4. Our company is reducing the time required to make decisions 5. Our company's organizational intelligence is designed to reach accurate and comprehensive information in a timely manner 6. Decisions are more consistent between various departments in our company		
Operational performance (OPP)	*Please indicate the level of your agreement to the following statements that are related to the effects of BA applications on your firm's operational 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 to 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)
Financial performance (FIP)	*Please indicate the level of your agreement to the following statements that are related to the effects of BA applications on your organizational 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 costs have 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 costs have 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)

Declarations

Competing Interests ☒ The authors declare that they have no known competing or financial interests, or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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