Effect of Business Intelligence and Analytics on Business Performance

Full papers

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Abstract

This article examines the relationship between extent of business intelligence and analytics (BI&A) implementation and business performance. Also, it analyzes the moderating role of technology in this relationship. The data for our model is collected from secondary data sources for 116 public companies in United States. The data is analyzed using structural equation modeling techniques. Our findings show positive relationship between extent of BI&A implementation and business performance. Furthermore, our results show that type of BI&A has significant moderating impact on the BI&A implementation and performance relationship.

Keywords

Business intelligence and analytics, business performance, data analytics, big data

Introduction

Business intelligence and analytics (BI&A) and the related field of big data analytics have become increasingly important in both the academic and the business communities over the past two decades (Chen et al. 2012; Davenport 2006). BI&A are set of tools and techniques which help transformation of raw data into useful information for business analysis purposes. BI&A provides business with identification, development or creation of new strategic business opportunities which results in sustainable competitive advantageous (Rud 2009). BI&A aims to identify and process data flows into relevant knowledge for managers to enhance the decision making in different layers of business. In the ranking of most significant IT investments, investment in BI&A is ranked highest in past few years. Based on Gartner report, investment in BI&A increases annually (Gartner 2013). In another research by Kappelman et al. (2013) on a large sample of American companies, BI&A has always been one of the top three IT investments in the period of 2003 to 2007 and in the period of 2008 to 2013, it had the first rank. Also, Kappelman et al. (2013) report that BI&A has a high rank in CIOs worrisome technologies list. Because of the substantial increase in BI&A investment, many authors discuss that it is important to measure the outcome of investment in BI&A (Solomon 1996). In contrast with the importance and increasing investment in BI&A, the understanding of why and how BI&A impacts firm performance is still incomplete (Trkman et al. 2010). To address the void, we investigate the impact of BI&A on business performance. Also, some of the important moderating variables that have impact on the relationship between BI&A and business performance are studied.

Chen et al. (2012) argue that today data is getting ubiquitous and cheap and analytics is complementary tool to create value from available data. Therefore, it is a unique opportunity for companies and they try to benefit from BI&A. In contrast with this importance, the literature lacks a rigorous method to measure BI&A and the real business value of BI&A is not discussed sufficiently (Lönnqvist et al. 2006; Solomon 1996). Due to importance of BI&A for business and increasing investment in the related technologies and infrastructure, it is necessary to determine the payoff of this investment. This paper fills a gap in literature by evaluating the impact of BI&A investment in business performance. The proposed model in this paper is analyzed based on secondary data.

The remainder of the paper is organized as follows. In the next section, the problem is discussed based on the literature. Then, the research model is developed. The model and hypotheses are further discussed and expanded based on literature. Next section, data measures are discussed and justified, the method for data collection is described and the model is analyzed based on the collected data. Then the model reliability and validity are evaluated. The next section discusses research findings and contributions. Finally, conclusion it presented, limitations are discussed and opportunities for future research are introduced.

Background

Lönnqvist et al. (2006) state that the common reasons for measuring BI&A is that decision makers need to know how worthy BI&A is for investment. Furthermore, it is important to figure out the mechanism that BI&A results in enhancing the business performance. Determination of its different aspects and effect of each aspect on business performance helps BI&A users to improve its implementation practices. Although the topic is important, there are few studies on the impact of BI&A on business performance. We searched for business intelligence and analytics keywords in different databases and found few research studies that examine the relationship between BI&A investment and business performance.

Trkman et al. (2010) discuss direct relationship between business analytics in supply chain and operational performance. They considered the moderating role of business process orientation and information systems support. Sharma et al. (2010) analyze the impact of dynamic business analytics on competitive actions which in turn results in organizational performance. Shanks et al. (2010) assert that business analytics resources improve firm performance through value creating actions. Williams et al. (2010) examine the practical value of business intelligence through improving business information, analytics and decisions. The outcome of this improvement is increased sales, reduced costs, and enhanced profits. Chae et al. (2014) investigate the impact of advanced analytics on operational performance. They conclude that advanced analytics improves operational performance through improved supply chain management initiatives and enhanced manufacturing planning quality. Based on a literature review, Lönnqvist et al. (2006) identify and assess measurement approaches for value of BI, but they do not conduct any empirical study for their proposed approach. Seddon et al. (2012) propose a model to explain how business analytics contribute to business value. To complete their research, they performed a primary test on 100 customers' success story. These customers are restricted to IBM BI tools. Sidahmed (2007) develop an assessment framework to analyze the impact of business intelligence capabilities on organization performance. Yogev et al. (2012) develop a research model that describe the effect of business intelligence on improvement of business performance. They analyze data which is collected from 159 managers and IT/BI experts, using Structural Equations Modelling (SEM) techniques. Their analysis shows that BI largely contributes to business value by improving both operational and strategic business processes.

Among these studies, Trkman et al. (2010) and Yogev et al. (2012) performed a survey and validated their model, but the other studies just based their results and conclusion on the literature review. In addition, these studies had limitation in their scope. Therefore, it is important to cross-validate these research results. Another important factor that needs to be addressed in the literature is detailed description of impact of BI&A on business performance. This could be achieved by defining moderating variables for BI&A. None of the previous papers considered the moderating role of type of BI&A in this relationship.

Theory Base and Research Model

To fill the gap in literature, this research is going to answer two questions. First, what is the effect of BI&A on business performance. Second, what are the variables that moderate the relationship between BI&A and business performance. Figure 1 presents the proposed model, which integrates relationships between different constructs that have been established in the literature. Within this model, BI&A implementation impacts business performance and type of BI&A moderates this relationship.

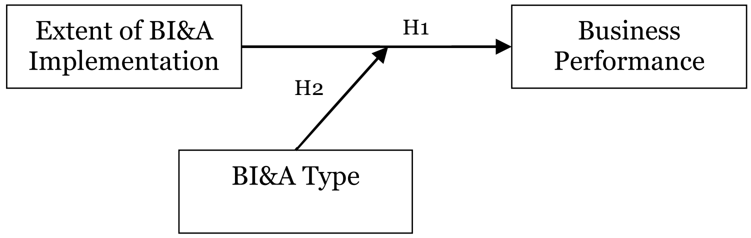

Figure 1: Research model

Business Performance

Today the concept of performance is discussed in different management disciplines (Neely et al. 2005). A review of research in this area reveals that while performance is widely used in the literature, there is no generally accepted definition and measurement for performance (Yıldız et al. 2012). Each definition comes from a specific perspective and is based on the context and features of a business performance system (Franco-Santos et al. 2007). Neely et al. (1995) define business performance as "the set of metrics used to quantify both the efficiency and effectiveness of actions" (p. 81). Yıldız et al. (2012) identify profitability, sale growth, market share, new product launch, return on sale (ROS), return on investment (ROI) and customer satisfaction as the most important quantitative criteria for business performance. In the marketing management literature, a combination of profitability, sale growth, and market share are used as common measures for business performance (Nwokah 2008). Operations management researchers use profitability, market share, customer satisfaction, ROS and ROI as a proxy for business success measurement (Whitten et al. 2012). Research in the information systems context also has specific business performance measures including profitability performance and sales performance (Salleh et al. 2010). We follow the discussions in literature and incorporate ROI, ROA, ROE, ROS and market share that are repeatedly used in different disciplines as a measure for business performance.

Extent of BI&A Implementation

BI&A are a range of technologies that aim to use information as a strategic tool for competition (Davenport 2006). To use these technologies, companies need appropriate hardware infrastructure, shared data and knowledge creation technologies (Kretzer et al. 2014). Therefore, it is important to adopt technologies to improve the implementation and interpretation of information across the supply chain (Gunasekaran et al. 2004). Companies need to invest in technological infrastructure that is necessary for their BI&A requirements. The infrastructure is an enabler for appropriate information use towards improvement of business, enhancement of sales and marketing, and elevation of business performance (Kauffman et al. 2012). In the current research, we use extent of BI&A implementation as a proxy for investment in BI&A. Also, we use it as a measure for analytical abilities of the firm. BI&A investment identifies the access of the company to required infrastructure that enable the firm to implement the related tools and techniques which are required for improvement of business performance (Oliveira et al. 2012).

Type of BI&A

This construct is a categorical measure for analytical capabilities of a company in different application levels. There are three types of BI&A technologies for treating todays data analytics needs (Chen et al. 2012) and this paper considers these three types as primary way for responding to the specific needs of business. This method is consistent with literature. Two examples of using this approach in literature are as follow. Davis-Sramek et al. (2010) consider the level of analytical tools used for assessing the relationship between supply chains. Chae et al. (2014) used type of tools that are used in analytics as measures for analytics.

Hypotheses

Three different justifications are employed to discuss the effect of BI&A on business performance. First, the effect of BI&A on business performance is discussed based on literature. Being equipped with an appropriate level of information technology infrastructures as well as knowledge creation enables organizations to improve performance (Kuglin 1998). BI&A tools provide the users and decision makers with the ability to create customized reports which serve as their specific business needs. Thus, BI&A is expected to enhance performance through providing insight into business operations for business users (Kohavi et al. 2002). Analytical abilities improve human decision making in different business processes and as a result enhanced the business performance (Trkman et al. 2010). BI&A is discussed to have positive impact on different aspects of business performance. For example, Saxena et al. (2013) suggest that analytics improves sales performance. Germann et al. (2013) discuss the importance of marketing analytics and its impact on business performance, sales performance, and other financial indexes. Verbraken et al. (2012) propose that implementation of marketing analytics will result in better understanding of customer needs, providing more customized products and services for them and enhance the customer base or benefit margin.

Second, technology investment which is discussed in literature serves as a similar topic for BI&A. While there is limited direct discussion about effect of BI&A and financial measures that construct business performance, Rai et al. (1997) state that technology investment improves ROA and ROE. There are other studies that suggest the impact of technology investment on business performance measurement items including (Kohli et al. 2012).

Finally, the impact of BI&A on business performance could be studied through the lens of established theories like resource based view of the firm. The RBV indicates that knowledge that is the result of supplier and customer collaboration is a unique resource and results in competitive advantage (Rungtusanatham et al. 2003). Therefore, the first hypothesis is related to effect of extent BI&A implementation on business performance.

> Hypotheses 1: Extent of BI&A implementation is positively related to business performance.

In addition to discussions about the role of BI&A implementation on business performance, there are research papers that discuss the higher effect of newer BI technologies (BI&A type) on business performance (Malhotra 2005). Trkman et al. (2010) discuss that application of different BI&A tools will result in improving different aspects of business performance. To analyze the moderating effect of different BI&A technologies on the relationship of BI&A and business performance, we propose the second hypothesis as follows.

> Hypotheses 2: BI&A type moderates the relationship between Extent of BI&A implementation and business performance.

Methodology

Data and Variables

We test the proposed hypotheses based on secondary data sources that are available for US companies. The data for each company that is studied in this research is collected from four different sources. The data needed for business performance is extracted from Compustat. Compustat is a database that includes financial and market information for global companies. ROI, ROA, ROE and ROS are computed based on the available measures from the North America Compustat dataset. Authors could not find any valid measure for market share in the literature. Consequently, a measure is developed for market share to serve the purpose of this paper. There are two challenges for developing this measure. First, each company might have a range of products and each product might sell in a specific market, therefore it is not possible to determine a single market share measure for a company. Second, even two companies that are in the same industry code (NAICS) might have different markets for their products and do not compete directly. Therefore, instead of considering the market share for products, this measure is developed based on financial share of market. The proportion of sale in a specific industry section is used as a measure for market share (gross sale divided by total gross sale of the industry sector). This measure shows relative firm size and serves the purpose of measuring the effect of availability of data sources on business performance.

Data related to BI&A type was collected from LexisNexis and INFOTRAC Newsstand. LexisNexis has the largest dataset of public records information. INFOTRAC Newsstand is a full-text database for newspapers. The purpose of this data is to examine types of BI&A that is used in each of the studied companies. To extract the data from these two datasets, a set of keywords for each BI&A type is determined. BI&A has three types. Any basic BI&A technology is considered to be type one. To determine if the companies benefit from type two and three, the content of the two datasets were searched based on keywords in Table 1 (Chen et al. 2012). BI&A type consists of three levels (type one, two and three). Dummy variables are used for measurement of BI&A type. The dummy variable is considered to be 1 for those companies that used the related technology (based on evidences from the two datasets) and it is considered 0 if no evidence is found.

BI&A 2.0	BI&A 3.0
• Information retrieval and extraction • Opinion mining • Question answering • Web analytics and web intelligence • Social media analytics • Social network analysis • Spatial-temporal analysis	• Location-aware analysis • Person-centered analysis • Context-relevant analysis • Mobile visualization & HCI

Table 1: Keywords used for searching BI&A type in the content analysis

There is no direct measure for extent of BI&A implementation in secondary data sources. Information systems researchers have the same problem while working on measuring returns on investment in IT. Some of the IS researchers used labor data as a measure for investment in IT to resolve this issue. Tambe and Hitt (2012) use the number of human resources in IT department as a measure of investment in IT. There are other studies that used IT labor data as a measure for IT investment. Lichtenberg (1995) used a secondary data source to measure the output contribution of information system labor in firm performance. Brynjolfsson et al. (1996) discuss that IS labor spending generates at least as much output as spending in non-IS labor. Inspired by the idea of indirect measurement of IT investment through labor statistics, this research uses number of human resources in BI&A as an indirect measure for extant of BI&A implementation.

Data needed for level of BI&A implementation is collected from LinkedIn website which is in accordance to literature. To verify that the collected data is representative for extant of BI&A implementation, two criteria are discussed. First, it is shown that LinkedIn data is a good representative of US companies and employees. Second, it is shown that there is a significant positive relationship between extent of BI&A implementation announcements and number of BI&A related employees in each company.

- Representativeness of LinkedIn data: US have 158 million active workforces and LinkedIn has 107 million members in US, therefore LinkedIn is considered as a good representative for proportion of active workforce in BI&A to the total workforce in each company. To verify the representativeness of LinkedIn data, the collected statistics from LinkedIn is compared with Current Population Survey (CPS) (from United States Census Bureau, 2013). CPS results show that 0.1389% of active American employees work in BI&A positions. This percentage is calculated based on number of employees in five different occupational categories including “Computer and information research scientists” and “Operations research analysts”. The findings from LinkedIn show that 0.1302% of active American employees currently work in BI&A related position (October 2014) which is relatively close to the results reported by CPS. The method for extracting data from LinkedIn is discussed in following sections.
- Direct relationship between extent of BI&A implementation and related employees: There is a body of literature that uses announcements in secondary data sources as a means of measuring the investment. For example, Ranganathan et al. (2006) used ERP implementation announcements to measure the business value of IT investment. The use of announcements in other IS investment evaluations, inspired us for using announcements in BI&A as a measure for extent of BI&A implementation (a dummy variable). Based on the collected data, there is a significant relationship between BI&A related announcement on INFOTRAC Newsstand and LexisNexis and number of BI&A related employees. The R-square for the relationship between number of employees in BI&A and related announcements is 0.54 with p-value less than 0.001 which shows the significance of the relationship.

While announcements are just an indicator for implementation of BI&A in an organization, they do not reveal the extent of implementation. Considering the positive relationship between number of BI&A employees in a company and number of BI&A announcements, this paper assumes that the number of BI&A labor is a measure of Extent of BI&A implementation in each company. A major challenge in determination of right number of BI&A employees in a company based on LinkedIn search is determination of right keywords for search. To find the right search keywords, two major communities of BI&A in LinkedIn (with more than 100000 members) were analyzed and searched for the job titles. Total number of 78 unique job titles were found. Further refining the job titles, 7 keywords/phrases are found to be uniquely used in these job titles including: (1) business intelligence, (2) data scientist, (3) analytics, (4) data analyst, (5) data mining, (6) big data, and (7) data engineer. For each company in the analysis list, each of these job titles is searched for identifying the number of related employees.

Selection of Dataset

We observed substantial differences between distinct industrial sectors in term of using BI&A and business performance in our early analysis. Due to this basic difference, this search is focused on companies in one specific sector to do a more meaningful comparison and achieve more relevant results. Companies in information sector (NAICS code 51) are selected for this analysis. Based on United States Census Bureau (2014), "the Information sector comprises establishments engaged in the following processes: (a) producing and distributing information and cultural products, (b) providing the means to transmit or distribute these products as well as data or communications, and (c) processing data". This sector seems to be a very good match for this research since the companies that are active in this section (software publishers, web sites, telecommunication industries, broadcasting institutes, web search portals and data processing industries) have great potential to improve their performance using analytical tools. The data for total number of 116 US based high income companies from information industry was collected. Table 2 summarizes the collected data.

Construct	Variable	Mean	Std. Dev.	Description
Extent of BI&A implementation	Extent of BI&A implementation	8.61	7.45	Total number of BI&A related workforce divided by number of employees multiplied by 1000.
BI&A type	Type one	0.93	0.26	It is defined as 0 and 1 and any organization that has the BI&A workforce is assigned 1 and 0 otherwise.
	Type two	0.28	0.45	It is defined as 0 and 1 and those organizations that have any evidence for second type of the BI&A are assigned 1.
	Type three	0.28	0.45	It is defined as 0 and 1 and those organizations that have any evidence for third type of the BI&A are assigned 1.
Business performance	ROI	0.07	0.07	Return on Investment
	ROA	0.16	0.16	Return on Assets
	ROE	0.13	0.14	Return on Equity
	ROS	0.53	0.14	Return on Sale
	Market Share	0.12	0.18	Total Sale divided by sum of Total Revenue from sale for companies in the same market.

Table 2: Descriptive statistics for key variables

Analysis Tool

The research model that is presented in Figure 1 is analyzed using SmartPLS (v.3.1.6). SmartPLS is a software application for graphical path modeling with latent variables that uses the partial least squares (PLS)-method (Ringle et al. 2014). This tool allows analysis of interaction between different variables.

Checking Reliability and Validity

Table 3 shows reliability results of testing measurement model. Market share shows unexpected and unacceptable low outer load. Based on Wong (2013), indicator reliability is acceptable for 0.4 or higher for exploratory research. Therefore, market share is dropped and the rest of items that are shown to be acceptable are used to measure constructs.

Latent Variable	Indicators	Loadings	Indicator Reliability	Composite Reliability	AVE
Business Performance	ROI	0.914	0.835	0.804	0.635
	ROA	0.792	0.627		
	ROE	0.744	0.554		
	ROS	0.724	0.524		
Extent of BI&A implementation	Extent of BI&A implementatio n	1.000	1.000	1.00	1.00

Table 3: Assessment summary for the model

All the latent variables in Table 3 have composite reliability value that is larger than 0.6, therefore high type of internal consistency reliability is demonstrated among the three constructs. For AVE, all the latent variables have larger values than 0.5 which confirm the convergent validity. Results in Table 4 show that all diagonal values are larger than off-diagonal elements and support the discriminant validity.

	Extent of BI&A implementation	Business Performance
Investment in BI&A	1.000	
Business Performance	0.604	0.713

Table 4: Assessment of discriminate validity

Results and Discussion

In these analyses, all the business performance measures are considered in the form of one latent variable (business performance). Since these variables are presented as single item constructs, adding them to these analyses does not affect the results. Results of running bootstrapping algorithm support the first hypothesis. In analysis of structural model, the path dependence between "extent of BI&A implementation" and business performance is significant at 5% level. The path coefficient for this relationship is 0.434 which is able to describe 39.6% of the variability in the exogenous variable. This relationship is shown in Figure 2.

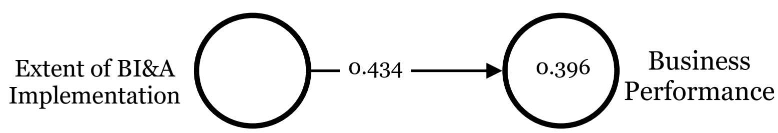

Figure 2: The structural model with path coefficients

As presented in Table 6, all t-statistics are larger than 1.96 and therefore the model loadings are significant.

Moderating Effects	Moderating Effects	Moderating Effects
Extent of BI&A implementation	Extent of BI&A implementation	Single Item Construct
Business Performance	ROI	29.1
	ROA	11.9
	ROE	8.6
	ROS	11.3

Table 5: T-Statistics for outer loadings

To analyze the moderating role of BI&A type on relationship between BI&A implementation and business performance, we conducted a group analysis. In this analysis, we divided our data into two groups based on the value of BI&A type. Table 7 presents the results of comparison. For each of the BI&A technology types, we used the data for each group and fitted the model to it. We estimated structural model to investigate the effect of BI&A implementation on business performance based on the data from these two groups separately. The relationship is depicted in Figure 3.

BI&A Technology *	Lower Levels of Implementation **	Higher Levels of Implementation **
Type 2	0.258	0.701
Type 3	0.222	0.520

* Type 1 is not included since the majority of the samples already have type 1 BI&A and the results are similar to the main structural model.
** Sample size for higher levels of implementation for both type 2 and type 3 is 32 (84 companies are at lower levels). The number of mutual firm in the two sample is 19 companies.
*** All loadings are significant at 0.01 level.

Table 7: Path coefficient and t-values for different types and levels of BI&A and their moderating effect on business performance

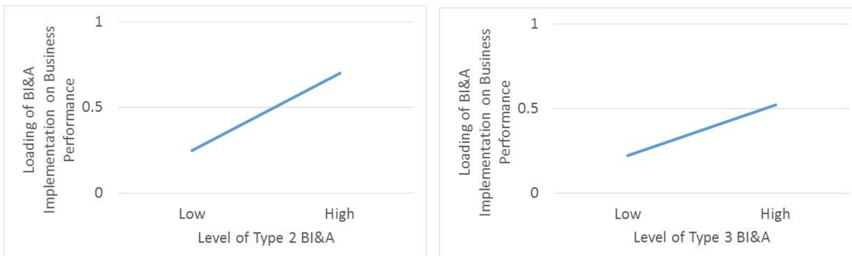

Figure 3: Relationship between model constructs at different levels of BI&A type

This study explores the synergy between BI&A tools and their effect on "business performance". Each part of these relationships is discussed based on literature separately for developing the model. The results support both developed hypotheses.

Discussion and Implication

The proposed model is analyzed based on the measures that are quantified from secondary data sources. The most important finding of this paper is the empirical support of significant positive relationship between extent of BI&A implementation and business performance. Furthermore, the results support the moderating role of BI&A type on this relationship. We also measured the direct relationship between extent of BI&A investment on each of the items that are loaded on business performance and found significant relationship between the factors. The analysis results show that BI&A improves business performance through improving ROI and ROE. In other word, as it is discussed by literature, BI&A improves the decision making process which result in better implementation of resources. Furthermore, there is evidence (at $p<0.1$ level) that BI&A improves ROS. In other words, BI&A enables organizations to focus on the marketing process. Our analysis did not reveal relationship between extent of BI&A implementation and ROA. Findings about the different types of BI&A and their effect on business performance are significant. Our analysis shows that type 2 BI&A which includes technologies like web mining and social media analysis have the highest impact on the improvement of business performance. Also, firms that are equipped with Type 3 of BI&A including analytical tools for sensor data outperform those who do not use such technology.

This research contributes to the literature by proposing a model that provides an integrated view of these related elements. Prior research argues that BI&A improves the performance and business value without empirical investigation. The other contribution of this paper is proposing proportion of workforce in BI&A related position to total employees as a measure for extent of BI&A implementation.

Although the research has important implications in practice, it should be considered that it faces a number of limitations. First, we selected information industry for data collection to make our data homogeneous. Therefore, the results are based on information industries which make it hard to generalize the findings to other industries. Furthermore, as mentioned in this section, different industries respond in different way to extent of BI&A implementation. Thus, there is a need for detailed investigation on the causes of this phenomenon. Another important limitation of this research is that due to the nature of collected data, the analysis was unable to consider the effect of time on business performance. Normally, each implementation and investment has its own payoffs after a time lag. But the available data is not able to reveal this time lag effect. The next limitation is focusing the research on US firms. Due to difference in some BI&A terms used in US and Europe, more sophisticated methods are required to extract the number of employees in BI&A. Furthermore, since the proportion of LinkedIn members to the total number of workforce might differ in different countries, the current method of data collection is not able to create a good basis for comparing companies from different countries.

Conclusion

The results of this study support the positive relationship between extent of BI&A implementation and business performance. This study developed a model based on literature and proposed 2 hypotheses. To evaluate the model, a sample of 116 companies in information industry is analyzed. The measures for this sample are quantified based on secondary data sources. All the basic controls for testing the reliability and validity of the model were performed and found that the model does not confront any major issue. Based on this analysis, both hypotheses are supported. BI&A improves the business performance. Also, type of BI&A technology moderates this relationship. Being empowered by second and third generations of BI&A improves the overall performance of the firm. More specifically, firms that are equipped with analytical tools for analysis of web and social media have higher association between their extent of BI&A implementation and business performance. Also, companies that collect and analyze sensor data outperform those who do not.

The major contribution of this paper is use of human resource data as a proxy for measurement of extant of BI&A implementation. We recommend that in future research, use of human resource data should be further justified to be used as a proxy for BI&A investment. There are several interesting and important topics that need further discussion in future works. It is important to further analyze the representativeness of labor data for extent of BI&A implementation. Comparing the results across different industry sections and discussing the role of BI&A in each industry section is another interesting topic. Another useful approach to study the relationship between BI&A and business performance is development of panel data with enough number of study periods. This approach is useful in analyzing the effect of time gap on extent of BI&A implementation.

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