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Leveraging Business Intelligence for Organizational Performance the Emerging Economy Context

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ABSTRACT

Business intelligence is a promising style extensively used in decision-making processes. The application of Business Intelligence (BI) is growing at an incredible rate in developed countries but its exposure in emerging economies, like India, is still low. The impact of business intelligence technology on the decision-making process and ultimately on the organizational performance has been studied by many authors in various economies, but still, is a subject to be investigated in India. There are studies that say emerging markets are going to be new drivers of economic growth in upcoming future. This study is an attempt to evaluate the impact of business intelligence technology achieved by organizations in an emerging economy i.e. India. A previously developed survey instrument was used to collect data from decision makers and BI users from different companies that are operating in India. The data analysis was done with the help of PLS-SEM technique. The study found the impact of business intelligence on determinants that are responsible for organizational performance benefits to be achieved by organizations in India.

Keywords: Business Intelligence, Organizational Performance.

INTRODUCTION:

Today, business managers all over the world need timely and accurate information in order to make effective decisions in the current highly competitive business environment. Business Intelligence (BI) systems have the potential to help business managers in a rapid and efficient decision-making process by providing the right information to right people in real time. According to a survey study, organizations earn $13.01 for every dollar spent (Nucleus Research, 2014). That is almost 1300% ROI of BI & Analytics applications.

Porter & Miller (1985) had identified the importance of Information Technology (IT) in the operating of organizations and mentioned that dramatic reductions in the cost of obtaining, processing and transmitting information are changing the ways of doing business. By delivering accurate information in real time or at the correct point of time to decision makers overall performance of an organization can be improved.

By improving the performance organizations can create value for its stakeholders. The term “Value” can be understood by the definition; “Value is the capacity of a good, service or activity to satisfy a need or provide a benefit to a person or legal entity”, Baier (1966). Thus achieving a benefit or satisfaction of a need can be understood as value created.

Today, the importance of analyses of historical data has amplified in order to have a closer look at the inaccuracies occurred in past. Indian organizations also now understand the hidden potential of BI as it can help leverage this data for further improvisation in business processes and decision making, thereby making business managers more efficient to create value for stakeholders. Also, the ever-increasing competition in the market has led to the adoption of decision-making enablers like BI which has led to greater improvements in overall performance of the organizations. This research is an attempt to measure the benefits achieved as a result of BI implementation in the Indian context.

LITERATURE REVIEW:

BI Evaluation has long awaited course for researchers as well as for business managers. The managers must want to know the worth of investments made by them. Researchers have attempted in this direction and proposed various models to evaluate or measure the effects a business intelligence system (BIS) can have on the overall performance of an organization. Few of them are explained below.

Lonnqvist & Pirttimäki (2006) conducted a research to determine the major purposes of business intelligence evaluation and suggested improvements in the then used BI measurements. The study highlighted two important reasons to measure BI. The first and very basic motive behind BI evaluation is to provide evidence that BI is worth investment (Sawka, 2000). Another important requirement of BI measurement is to help manage BI process, i.e. to make sure that BI products satisfy users' needs and that the process is efficient (Herring, 1996). The study suggested exercising a Balanced Performance Measurement system that could cover the effects of BI process and the important factors as well.

Better information, better strategies, better tactics and decisions, and more efficient processes were among the top five benefits considered most important in BI development. Little research has been identified describing how (if at all) these intangibles are identified and weighed, who the participants are, and how this is incorporated into BI business cases (Gibson, Arnott, & Jagielska, 2004).

In this regard, Gibson et. al. (2004) have addressed the methods used to evaluate intangible benefits of Information Technology (IT) and discussed their application to BI. Further, the research proposed an agenda to enhance domain knowledge in this area. The scant academic research on BI makes it hard to consider BI investment as same as other IT investments or to call for new evaluation methods considering it a completely different investment type (Surmacz, 2004; Gibson et. al., 2004).

There are various researches that consider BI as a different solution than IT and developed various measurement instruments to measure the business value of BI.

Gibson et. al. (2004) maintained that the strategic nature of business intelligence, the dispersion of its benefits throughout the business and its effects on business culture makes it difficult to be measured through traditional evaluation techniques. Apart from operational and efficiency benefits, information technology can offer payback at a strategic level which makes it even more difficult and challenging to clearly identify the business benefits of BI. Many evaluation techniques face difficulty while quantifying the intangible benefits of an investment. Intangible benefits include greater business knowledge, improved work process or more effective relationship which are sometimes not feasible to measure. The intangible benefits, especially of IT, are mostly ignored by the management. Counihan, Finnegan, & Sammon (2002) included that it is unsurprising that many traditional evaluation techniques continue to fail or provide misleading information especially when it comes to measuring non-traditional benefits.

Hatch (2011) stated that the supreme objective of an organization is to create value. The value creation is as important to measure as it is difficult to define. Creating shareholder value is perhaps the most tangible way of looking at value creation. One can see the financial indicators as a close view of value creation. The popularity of this concept lies in the fact that it is relatively easy to measure and calculate and criticized the idea of treating this concept as correct measure of success just because it's easy. On the other hand, Hatch (2011) considered profit as the most vital element for any organization to sustain and grow.

The use of business intelligence is vital in today's highly competitive world and no organization can refuse the advantages of using a business intelligence system (BIS) (Farrokhi & Pokoradi, 2012). According to Yogev, Fink, & Even (2012) the business value of information technology is mainly dependent on system type and therefore its evaluation requires a careful analysis of the unique manner by which each category of systems creates business value. Through a model based on Resource-Based View of the firm, their research concluded that business intelligence has a unique potential to generate both strategic and operational value by uninterruptedly integrating organizational data for decision making purpose at various levels. The research work also highlighted the need for evaluation techniques to examine mechanism through which value is created.

There are various models proposed and tested by different authors for IT business value measurement but the characteristics of business intelligence systems (BIS) are totally different from a traditional IT system. Therefore various authors have proposed specific models to measure the business value of business intelligence systems. The scant academic research on business intelligence makes it hard to consider BI investment as same as other IT investments or to call for new evaluation methods considering it a completely different investment type (Surmacz, 2004; Gibson, Arnott, & Jagielska, 2004) In this regard various authors have considered business intelligence as a different solution than IT and developed various measurement instruments to measure the business value of BI.

According to Hocevar & Jaklic (2010), use of BIS has numerous benefits which are difficult to measure because of their indirect and delayed effects on business success. It's hard to justify the investments made in information technology especially in business intelligence. It is also inappropriate and insufficient to use return on investment (ROI), cost-benefit analysis, net present value (NPV), internal rate of return (IRR) and other classical methods alone for evaluating an investment in BIS. To get a clear view of business benefits of BI, Hocevar & Jaklic suggested a combination of any of these methods with a qualitative approach e.g. case study, empirical analyses and user satisfaction analyses. The concept of evaluating each BI case on an individual basis according to circumstances and purpose of the evaluation is strongly supported. Through a case study of evaluation of investments made in online analytical processing (OLAP) technology, the authors have analyzed user's opinion along with a strategic analysis based on identifying a cause-effect relationship between the benefits of OLAP technology and strategic goals of the company. The authors concluded that qualitative methods such as strategic analysis and an analysis of users' subjective assessments are appropriate for evaluating investments in BI.
Yeoh & Koronios (2010) studied and identified Critical Success Factors for business intelligence system success and implementation in transportation and utility industry. With the help of Delphi study, a number of Critical Success Factors were identified that are necessary for implementing a Business Intelligence system. The research work concluded that BI life cycle includes a cyclical evolution due to changing business environment and identified success measures and categorized into two main sections i.e. Infrastructure Performance and Process Performance. Infrastructure performance includes system quality, information quality, and system use while process performance consists of budget and time schedule.
Mutschler, Bumiller, & Reichert (2005) have proposed a valuation model to quantify the benefits of business process intelligence (BPI). The research proposed two different BPI specific cost models that are supposed to quantify the total costs of ownership of BPI investments and the positive impact of BPI on software development projects. They have considered the cost of the BPI investment as an important factor. According to them to quantify the benefits and costs of BPI tools is practically complicated because costs cannot be clearly associated with single cost factors, benefits are hard to evaluate and risks are not conceivable. In their research, they have excluded the analysis of risk of using BPI tools.
Elbashir et al (2008) have segregated business intelligence from other IT means and have developed an instrument to measure the business value of business intelligence by extracting the relationship between business process level and organizational or strategic level benefits being achieved as an impact of business intelligence systems. The research work pointed out that it is challenging to identify the contribution of information technology due to its unique nature, diverse applications, and tangible and intangible impacts. These attributes demand a performance measure that is specifically developed for the technologies concerned and consistent with management objectives and business plans regarding IT (Mooney, Gurbaxani, & Kraemer, 1995). Elbashir et. al. (2008) have emphasized that using accounting measures such as return on investment (ROI) while evaluating business performance of a transactional processing system (TPS) would not be appropriate because such measures are mostly inconsistent with firm's strategic intention regarding technology and significantly distant to the immediate influence of such system. The study argued that BI systems are deployed by the management to improve decision making and competitive advantage and integrated effectively into management and operational processes. Therefore, the performance impact of BI systems could be reflected on at least two levels i.e. internal strategy and competitive strategy. The adopted model has considered both the levels for measuring the impact of BI.

METHODOLOGY:

This is an exploratory study as there is little prior evidence and knowledge on how the variables are related. This study used previously developed and validated survey instrument. According to Trochim & Donnely (2006), data collection through surveys is effective if the survey instruments have been previously developed and validated. For the purpose of data analysis and to test complex relationships partial least squares structural equation modeling (PLS-SEM) was chosen as PLS-SEM has the ability to support latent variables that are directly unobservable. Also, the early stage of model development compelled to use PLS-SEM in this research (Hair, Hult, Ringle, & Sarstedt, 2014). PLS-SEM technique has been extensively used for testing exploratory conceptual models in the field of business intelligence (e.g. Elbashir et.al., 2008; Popovič et.al., 2012; Ramakrishnan et. al., 2012; Spark, 2014). Structural equation models (SEM) perform well for theory testing as well as for testing measurement models (Bagozzi, 1980). Partial Least Squares (PLS) is the most appropriate procedure to use for small sample sizes.

RESEARCH OBJECTIVES:

This study is assumed to counter the following research objectives;

- To study the performance effects of business intelligence system usage at the business process and organizational levels in organizations in India.
- To what extent the performance effects at the business process level are reflected in organizational level performance in organizations in India.

Measurement/Survey Instrument:

The model developed by Elbashir et al (2008) is theoretically based on Michael Porter's value chain activities framework. In order to measure the effect of BIS at the organizational level and within the business process, value chain activities were broken down into 22 variables out of which 18 variables remained after confirmatory factor analysis. The measurement instrument was rigorously developed according to Churchill's (1979) methodology for designing and validating a construct. The constructs identified were business process performance, business supplier/partner relation benefits, internal process efficiency benefits, customer intelligence benefits and organizational (strategic) performance benefits. The research questionnaire consisted of 7 point Likert scale variables to measure the impact of BIS on those variables. All of the measures of research instrument showed a significant composite reliability. The convergent validity of the instrument was established by the values of factor loadings (t-statistics) and average variance extracted (AVE) greater than the recommended principle for a minimum score. The greater Square root of AVE than inter-correlations among constructs represented discriminant validity whereas content validity for the instrument was established through thorough literature review. The measurement instrument developed by Elbashir et. al. (2008) is technically and statistically sound therefore used in current research. The constraint of this research study was that all the companies selected as a sample in this study belonged to single BI software vendor but in the present study, respondent firms have chosen with convenience sampling and do not belong to a single BI vendor.

Data Collection:

The current study is a cross-sectional descriptive research. The universe for this research is the organizations operating in India and using business intelligence system in the decision-making process and the target population includes information technology (IT) professionals and top-level managers involved in the decision-making process through the use of BI, working for manufacturing or service industry in India. The samples are collected through convenience sampling. The population elements are selected on the basis of their availability and on the personal judgment that they are a true representative of the population. In association with convenience sampling snowballing was also used where existing respondents were requested to refer the questionnaire to their acquaintances in the related field.

A questionnaire was prepared using an online survey service provider. The questionnaire stands consistent with industry practitioners' opinions. One of the foremost reasons to go with Elbashir et.al.'s (2008) model lies behind the suggestions given by an industry expert for questionnaire development i.e. take BI as a business project and not as an IT project in order to successfully measure the value of Business Intelligence in the Indian context. Elbashir et.al.'s (2008) model stands fit this criterion. Social media played an important role in identifying and connecting with the respondents. A total of 728 suitable respondents were selected after reviewing and verifying their profile through social media (Linkedin). The official email ids of the respondents were retrieved from an online data provider company. The questionnaire was then administered to the respondents via web link attached to an email and through social media messaging. After 3 months from sending the questionnaire for the first time, 54 responses were received. Later a reminder and request mail was sent to remaining 674 respondents. A total of 99 responses were received in over a period of 6 months with a response rate of about 13.60%. Along with 24 responses that were the result of snowballing, a total number of respondents reached to 123, whereas 19 respondents were met in person. A total of 142 responses collected. All of the responses were collected through web link and hence were usable because a short filled questionnaire could not be submitted online. The respondents were set free from revealing their identity but to provide the name of the company they work for was mandatory.

Instrument Development:

The survey instrument used in this study is adopted from Elbashir et. al. (2008). The model is previously developed and validated by the authors. The survey instrument consists of 18 variables on a 7 point Likert scale with an additional "0". The respondents were supposed to mark "0" where there is no basis for answering.

Elbashir et. al. (2008) used PLS-SEM for analysis while developing the measurement instrument. PLS-SEM is designed to maximize the variance explained in all endogenous constructs, therefore most suitable for prediction and theory building purpose. It also does not put restrictions for normality of data distribution when compared to other SEM techniques like LISREL (Chin et. al. 2003; Chin, 1998; Mathieson et. al., 2001). PLS was used to estimate the validity and reliability scores of the measurement model: Reliability of the above model was consistent with factor analysis and Cronbach's Alpha and Composite reliability for all the measures lies between 0.82 and 0.92 (>0.70, acceptance limit). Content validity was supported by literature review, interviews, peer reviews, focus groups and other qualitative tests. Convergent validity was reflected in each factor loading of above 0.70 and AVE above 0.50. The measurement showed satisfactory discriminant validity as the square root of AVE was all greater than the inter-construct correlations.
Data analysis was performed with the help of PLS-SEM using Smart PLS 3 software package (Ringle, Wende, & Becker, 2015). The PLS-SEM is designed to maximise the variance explained in all endogenous constructs. The initial testing requires an evaluation of measurement model i.e. internal consistency reliability and validity. In this study, the measurement model is reflective in nature.

Reliability:
The internal consistency of the model was evaluated using Composite Reliability (CR). The CR scores of all the latent constructs have crossed the threshold value of 0.708, and have values lesser than 0.95 (Table 1).These values provide sound internal consistency, i.e. reliability, of the measurement model (Hair, Hult, Ringle, & Sarstedt, 2014). Higher outer loadings present higher reliability of all indicators variables. All of the indicators have outer loadings of more than 0.708 (Table 1).

Convergent Validity:
The Average Variance Extracted (AVE) value of more than 0.50 of all latent constructs indicates that each of the constructs explains more than 50% of the variation in the observed variables and hence there is no concern with convergent validity (Table 1).

Discriminant Validity:
The discriminant validity is established with the help of cross-loadings (Table 2) and Fornell-Larcker Criterion (Table 3). The outer loading of each indicator variable is higher than their loadings on other constructs (Table 2) that indicates suitable discriminant validity. According to Fornell-Larcker criterion, the square root of the AVE of each construct should be higher than its highest correlation with any other construct (Hair, Hult, Ringle, & Sarstedt, 2014). Table 3 shows the values of the square root of the AVE (values in the diagonal) are all greater than the inter-construct relations which show the satisfactory discriminant validity of the measures.

Table 1: PLS Measurement Model Loading and t-statistics*

		OL*	SD*	t-statistic	P Value
Internal Processes efficiency Benefits: (Composite Reliability=0.949, AVE=0.823)					
BV2	Improved efficiency of internal processes	0.910	0.020	45.722	0.000
BV3	Increase staff productivity	0.876	0.028	30.978	0.000
BV4	Reduction in the cost of effective decision-making	0.926	0.014	67.908	0.000
BV5	Reduced operational cost	0.917	0.019	47.188	0.000
Customer Intelligence Benefits: (Composite Reliability=0.907, AVE=0.764)					
BV7	Reduced marketing costs	0.913	0.017	53.283	0.000
BV8	Reduced customer return handling costs	0.819	0.028	29.452	0.000
BV9	Reduced time-to-market products/services	0.887	0.019	46.252	0.000
Business supplier/partner relation benefits: (Composite Reliability=0.945, AVE=0.777)					
BV6	Reduced inventory levels	0.771	0.044	17.637	0.000
BV10	Reduction in the cost of transactions with business partners	0.880	0.032	27.774	0.000
BV11	Improved coordination with business partners/suppliers	0.908	0.017	52.400	0.000
BV12	Improved responsiveness to/from suppliers	0.935	0.015	64.040	0.000
BV13	Increased inventory turnover	0.905	0.020	44.409	0.000
Organizational (Strategic) Performance: (Composite Reliability=0.929, AVE=0.685)					

		OL*	SD*	t-statistic	P Value
BV17	Increased revenues	0.796	0.054	14.802	0.000
BV18	Reduction of lost sales	0.804	0.039	20.791	0.000
BV19	Increased geographic distribution of sales	0.831	0.050	16.488	0.000
BV20	Enhanced profit margin	0.835	0.045	18.545	0.000
BV21	Increased return on investment (ROI)	0.876	0.033	26.714	0.000
BV22	Improved competitive advantage	0.821	0.052	15.725	0.000

OL = Outer Loadings, S D = Standard Deviation.

Table 2: Cross Loadings

	BS/PRB	CIB	IPEB	OB
BV2	0.467	0.373	0.910	0.294
BV3	0.554	0.592	0.876	0.319
BV4	0.472	0.460	0.926	0.299
BV5	0.482	0.471	0.917	0.373
BV7	0.459	0.913	0.513	0.419
BV8	0.470	0.819	0.437	0.302
BV9	0.455	0.887	0.427	0.464
BV6	0.771	0.428	0.414	0.168
BV10	0.880	0.453	0.488	0.317
BV11	0.908	0.443	0.492	0.363
BV12	0.935	0.531	0.513	0.422
BV13	0.905	0.465	0.494	0.282
BV17	0.270	0.361	0.268	0.796
BV18	0.350	0.342	0.302	0.804
BV19	0.261	0.345	0.251	0.831
BV20	0.263	0.371	0.236	0.835
BV21	0.343	0.398	0.331	0.876
BV22	0.272	0.425	0.351	0.821

Table 3: Square root of AVE (Fornell-Larcker Criterion)

	BS/PRB	CIB	IPEB	OB
BS/PRB	0.881			
CIB	0.527	0.874		
IPEB	0.546	0.527	0.907	
OB	0.357	0.453	0.355	0.827

DESCRIPTIVE ANALYSIS OF RESPONDENTS:

The respondents for this study are key decision makers of the organization, BI users, BI developers, IT managers and other important personnel from different departments who have access to the BI information and are involved in decision-making process. The knowledge and perception develop through experience gained over years with the specific domain. Out of total 142 respondents, one respondent has not marked his relative experience, making it work experience of 141 respondents only. Approximately 39% of the total respondents have work experience of "between 6 to 10 years". A very low percentage has been recorded with respect to work experience of "more than 25 years" i.e. 2% only. Respondents from different 25 industries participated in this study. Majority of respondents belong to Information Technology Services industry i.e. about 31%. Out of total 25 industries, respondents from 5 industries contributed about 7.05%, 11 industries contributed about 7.70% and rest 9 industries contributed about 85.92%. The respondents also present a fair distribution of various hierarchies in the organizations. About 11 percent respondents belong to top managerial level, 16 percent head of various departments, 50 percent managers, 11 percent software engineers or BI developers, and about 11 percent BI specialists.

EVALUATION OF STRUCTURAL MODEL:

The results of the structural model are presented in Figure 1, Table 1 and Table 4 which illustrates the relationship between business process level performance (BPL Benefits) of BI systems and organizational performance/benefits (OB). The path coefficients indicate positive and significant relationships between BPLB and its reflective factors i.e. Customer Intelligence Benefits (CIB), Internal Process Efficiency Benefits (IPEB), and Business Supplier/Partner Relation Benefits (BS/PRB). It also demonstrates a positive and significant relation between BPLB and OB. The amount of variance in the endogenous constructs explained by R2 values is indicative of the predictive power of the exogenous latent construct (Chin, 1998). R2 values for endogenous constructs IPEB, CIB and BS/PRB are significantly high. The R2 value for OB indicates that 20.8% of the variation in OB is explained by BPLB of BI systems. The results support the measurement model developed by Elbashir et. al. (2008) and provide strong support for both the research questions (see Section 3.1).

Figure1: The Performance Impact of BI System

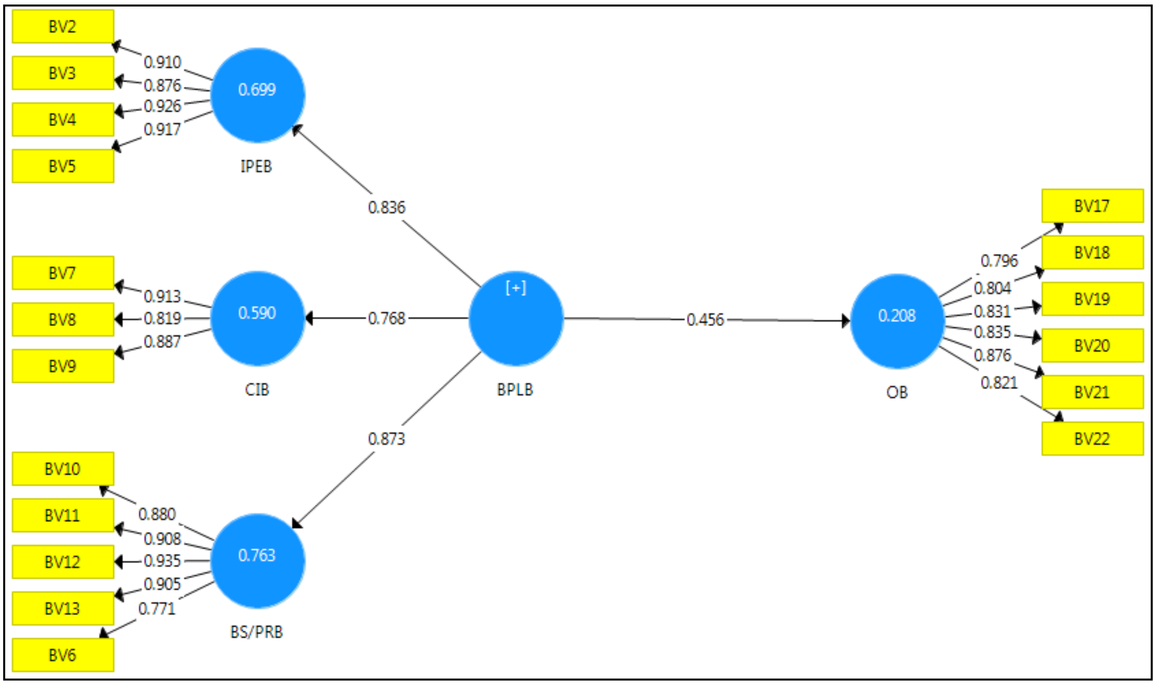

Table 4: Mean, STDEV, T-Values, P-Values (Bootstrapping)

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics * (|O/STDEV|)	P Values
BPLB -> BS/PRB	0.873	0.874	0.021	42.078	0.000
BPLB -> CIB	0.768	0.771	0.040	18.973	0.000
BPLB -> IPEB	0.836	0.837	0.045	18.594	0.000
BPLB -> OB	0.456	0.479	0.082	5.581	0.000

All Coefficients are significant at 1% (p=0.001), 5% (p=0.05), and 10% (p=0.01) levels of significance.

DISCUSSION, LIMITATIONS & CONCLUSION:

The study is an attempt to measure the contribution of BI system use in organizations in India. As expected, it appears that the BI system is significantly relevant for most of the management decisions, although the different amount of variability is seen in the relations between constructs. Remarkably, the decision makers, in general, are becoming dependent on the information provided by BI systems and are able to utilize the business analyses to counter strategic and operational challenges that may arise at any point of the value chain. BI systems have a significant impact on the various dimensions of the value chain activities.

Another interpretation is that, in India, the organizations started to rely on BI systems. The decision makers got a clearer understanding of the specific areas where any possibility of improvement exists. They are now making effective decisions with the help of BI systems and organizational performance is improved. One

In this study, it is assumed that all industries would have similar effects of BIS use, although, different industries may have different use of the technology and so the benefits. Hence further investigation is required. Another limitation comes with the sample size. A study with high sample size may reflect better results. Also, the data collection was a time taking process due to industry practitioners' negative attitude towards academic research. It was not easy to contact the concerned personnel of a company to get the questionnaire filled.

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