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Influence of Business Analytics Usage on Operational Efficiency of Information Technology Infrastructure Management

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ABSTRACT

Organizations today depend and thrive on timely, accurate and strategically relevant information. Business analytics (BA) holds the key to many of these issues. This paper validates a model on how the usage of BA leads to operational efficiency. We identified the factors of basic analytical usage from the Business Capacity Maturity Model (BCMM). The scope of the study is restricted to the Information Technology Infrastructure and Application management domain. A survey was conducted among the managers of the IT companies in Bengaluru, India. The results showed a significant influence of data-oriented culture and BA tools and infrastructure on BA usage. We found a significant influence of BA usage and pervasive use on operational efficiency. The speed to insight is still not practised in organizations. The awareness level of analytical skills in organizations is very low.

Keywords: Business Analytics, Operational Efficiency, IT Infrastructure, Application Management, Data Oriented Culture, Pervasive Use, Speed to Insight

Ⅰ. Introduction

Organizations depend largely upon Information Technology (IT) and IT-enabled Services (ITeS) to make business processes streamlined and efficient. Organizations today need to know about customers, markets, and processes faster than their competitors to capitalize on opportunities and deliver consistent sustainable business performance. Businesses need to go beyond the customary approaches to data and its management. Probably analytics is the answer. Business leaders across the globe are looking at analytics as a critical enabler for competitive markets. Business analytics (BA) is an advanced system that

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supports decision making. It includes acquisition, generation, assimilation, selection, and emitting knowledge required for decision-making (Holsapple et al., 2014).

IT infrastructure and application management are rapidly growing domains in Indian IT organizations, with many competitive players in the market; each organization wants to stay ahead. IT Infrastructure is a set of physical devices and software required to operate an enterprise, i.e., software, hardware, and networks. A standard IT infrastructure consists of broadly three categories - Data centres, Network, and IT end-user service. Businesses worldwide deal with considerable challenges to deliver improved service levels of IT infrastructure. They engage in a continuous effort to meet and override the expectations of their business users in terms of security, service quality, and time while optimizing resources and minimizing operations cost in the IT infrastructure management. Enterprise Infrastructure Management Services (IMS) need to achieve cost efficiency and rapid time-to-delivery. Organizations want to overcome this problem with many redundant tasks being executed and a huge amount of data collected daily. BA comes to the rescue.

Huge data is analyzed collaboratively across departments to get insight into the data and make smarter decisions (McKinsey, 2011). According to Industry analysts, organizations that utilize their structured and unstructured data effectively will outperform the competition by 20% in every financial metric. More and more business leaders are looking at analytics and information management technologies as critical enablers to outperform. Business analytics can turn information into insights by integrating and analyzing data in real-time. It offers greater transparency and increases accountability. Predictive analytics can avoid past failures, and future decisions based on facts can be smartly taken, leading to cost and time-saving.

The market size of the Indian Analytics industry in 2021 was $45Bn, which was more than 50% of the Worldwide BA market. The revenue was 26.5% more than the previous year. BA accounts for 23.4% of India's IT/ITeS business. Among the sectors, 43% of the BA market comprises the IT sector, followed by the banking and insurance sector with 13.9% (AIMResearch, 2021). Business analytics covers various domains and sub-domains within business administration areas like finance, marketing, human resources, operations, supply chain etc. (Holsapple et al., 2014). However, the application of analytics in IT service organizations is not straightforward. There are huge amounts of data in the range of terabytes/petabytes lying unused in silos. With different types of data available in the service operation domain, the spreadsheet-based analysis will not give the required strength to remain competitive in the IT services business. Kraan and Sherlock (2013) proposed that many organizations with a strong data-oriented culture, analytic expertise, and information systems make up for BA. There can be growth in revenues from analytics projects, especially in the banking world (Garg et al., 2017). Organizations can increasingly deliver value through BA, including people, processes, and technologies to enable data into insights that help future decision-making (Wixom et al., 2013).

Indian IT/ITeS sector is both provider and user of the BA. The benefits of the same need to be demonstrated to encourage the other industry to use the BA. The IT industry is predominantly a service industry and relies heavily on technology infrastructure and software applications. Therefore, there is a need for studying the dynamics of operational efficiency of the IT infrastructure and application management domain by utilizing BA.

This study aims to answer the question: Does BA usage influence the operational efficiency in the IT infrastructure and application management domain? The following objectives direct the study: 1) To find the influence of BA usage on the operational efficiency of IT infrastructure and application domain, 2) To investigate the influence of data-oriented culture, BA tools and infrastructure, and analytical competency on the usage of BA in IT infrastructure and application domain, and 3) To investigate the influence of BA usage, speed to insight and pervasive use on the operational efficiency of IT infrastructure and application domain.

Ⅱ. Theoretical Background and Hypotheses Development

BA combines technology and applied statistics to create quantitative models for a business situation, develop optimal solutions based on operations research, and interpret the results (Holsapple et al., 2014). Though these techniques existed in the past, Klatt et al. (2011) argued that technology development has intensified information overload, and analytical tools are necessary for successful decision support. Earlier studies focused mainly on the factors leading to the usage of BA (Burton-Jones and Grange, 2013; Burton-Jones and Straub, 2006; Kiron and Shockley, 2011). Kiron and Shockley (2011) recommended three key competencies for using BA by managers – data-oriented culture, BA tools and infrastructure, and analytical competency.

But how does the use of BA leads to organizational performance? Sharma et al. (2014) studied how the transformation of the decision-making process using BA create value for the organization. They proposed a model on how BA use and decision-making jointly affect organizational performance. Along with decision making processes, resource allocation processes, search and select capability, asset orchestration capability, and the governance structures enhance the organizational performance.

Business analytics usage, dynamic capabilities and strategic alignment between business and IT are proposed as the sustained business value that produces competitive advantage. The sustained value of BA is important for strategic performance and financial performance (Côrte-Real et al., 2019). Kiron and Shockley (2011) argued that the increasing trend toward analytics in business is driven by the need and the ability to use data to create business value and competitive advantage. The success and value of business intelligence and analytics depend on the intention to use and user satisfaction (Montero, 2019). Wixom et al. (2013) proposed that speed to insight and pervasive use are essential, along with BA usage for Operational Efficiency. Under the big data usage towards firm's performance, studies have found that data analytic capability improves both tangible and intangible benefits by helping the pervasive use of insights gained from its analytical capability (Akter et al., 2016; Anand et al., 2016).

The mere availability of resources cannot benefit the organization. Authors claim that "no use, no benefit!" Lautenbach et al. (2017) identified the factors influencing the Business intelligence and analytics usage extend based on the Technology-Organization-Environment (TOE) framework. Under the technology component, they proposed data-related infrastructure capabilities as a factor that influences the extent of BA usage. Similarly, many models such as knowledge-based view and resource-based view (Ghasemaghaei, 2019), Business Analytics Capacity Maturity Model (BACMM)

(Cosic et al., 2012), Technology acceptance model (Bayram, 2018) and DELTA plus model (Davenport, 2018) focuses on the maximum usage of BA.

Vidgen et al. (2017) argued that the key challenge for organizations is understanding how to leverage the BA and create business value. The authors recommend organizing the BA capability and aligning it with their business strategy through a Delphi technique and case studies to create value. There are limited studies that focus on combining the factors impacting BA usage and the value creation leading to organizational performance. Moreover, considering the prominence of the IT/ITes industry in applying BA and its dependence on the efficient utilization of the infrastructure and applications, there is a shortage of studies.

2.1. BA Tools and Infrastructure

The Enterprise Business Analytics Capabilities Model (EBACM) explains how BA capabilities are built, managed and changed (Wixom et al., 2013). Enterprise BA capabilities can establish high quality, usable, and integrated data. Decision-makers can utilize these data to solve critical business problems through various BA tools such as query, reporting and advanced analytics software and identify insights from data. It can trigger actions that generate a wide range of tangible and intangible business value.

Tools help to reduce manual work and automate the process. Business Analytics tools are third-party software that is intelligent enough to process structured and unstructured data from multiple sources in multiple formats and provide results. Analytics technology assets include "analytics tools, software and techniques, IT and ERP infrastructure, Software, BI infrastructure, and processes such as ETL, Data Sources and Data, and Reporting and visualization tools." (Krishnamoorthi and Mathew, 2018). Infrastructures are physical devices used in support of a BA environment. BA infrastructure consists of large storage space and real-time memory to process zeta bytes of data (in-memory processing capability).

Organizations reported particularly high adoption success and user enthusiasm with iPad-based BA deployments. Mobility leads to portability and ease of access to BA, leading to time-saving and increased productivity. As BA tools automate the manual data analysis process, BA tools and infrastructure may impact BA usage. Thus, we frame the following hypothesis:

H1: Higher availability of BA tools and infrastructure will have more usage of BA.

2.2. Data-oriented Culture

Davenport (2000) introduced the term data-oriented culture, which he recommends to enhance operational efficiency. Data-Oriented Culture is a pattern of data management practices, behaviours, governance and norms organized around a set of shared aims and beliefs. Analytical competence and BA infrastructure can create a difference between the organizations that possess them and those that do not. However, the difference between the organizations with similar analytics-oriented resources and capabilities will be the organizational culture that will support the use of data. Kiron and Shockley (2011) argued that in many organizations, there is a misconception that is simply having the right data in the hands of the right people who use the right tools is enough to create a competitive and performance advantage.

Mansell and Ruhode (2019) discussed organizational culture, including information readiness and information culture, as organizational factors affecting the usage of business intelligence. Specific studies in the supply chain that looked at barriers and archetypes in using big data and analytics argued that creating a data-oriented culture or data-driven culture is necessary for transforming the Organization capable of analytics. Félix et al. (2018) proposed changing the organizational culture to achieve the strategic objectives and create a data-oriented culture. Jeble et al. (2018) identified that the performance of organizations is influenced by technical skills, management skills, organizational learning and data-driven culture. Sharma and Sharma (2017) argued that HR analytics should promote data-oriented culture leading to fact-based decision making in appraisals. Data-oriented leaders must create competence that should be supported by recruiting analytical innovators and promoting analytical talents.

Data-oriented culture is defined as systematically managing external and internal data collaborating with different departments to derive its insight. IT infrastructure and application management departments generate a huge amount of data. However, the question is whether data availability leads to BA usage. Thus, we frame the following hypothesis:

H2: Higher data-oriented culture will lead to more use of BA.

2.3. Analytical Competency

Organizations to excel at using analytics and to create a competitive advantage depend on analytics expertise. Analytical competency is the organization's capacity to utilize BA tools and infrastructure. It includes processes and skills in transforming data into better value. Analytical competencies of the firms influence their efficiency. Ghasemaghaei et al. (2018) proposed the framework of analytical data competency based on Resource-based View (RBV) proposed by Bharadwaj (2000). It included data quality, the bigness of data, analytical skills, domain knowledge and tool sophistication. Analytical expertise is developed within a specialized line of business or functionally focused approach to analytics, such as deepening analytic skills within operations, finance and marketing to optimize and predict specific business processes. However, building analytical competencies takes time, posing distinct challenges (Kiron and Shockley, 2011).

Analytical competency includes numerical analysis, statistical analysis, and data science. BA tools give output based on input data. Experts with domain knowledge, decision-making ability, and skills to visualize the situation from broader aspects help correct, enrich, and make meaningful interpretations of the output. BA tool's output is analyzed using analytical competencies. The question is, how far is the availability of analytical competency lead to BA usage. Thus, we frame the following hypothesis:

H3: The higher presence of analytical competency will lead to more usage of BA.

2.4. BA Usage and Operational Efficiency

Value of IT is measured by performance metrics on dimensions that stakeholders find important. CIOs use certain metrics to manage their organizational units and drive IT/business conversations. Three distinct performance areas in underlying performance drivers are: (1) Operations metrics capture the performance of existing infrastructure and business processes. These typically include reliability, cost, and quality of operational execution. Quality is measured in terms meaningful to stakeholders, such as defect rates, satisfaction, or willingness of customers to recommend a service to others, (2) Project metrics capture the successful execution of change activities. Most organizations aim to meet or exceed schedule and cost goals and the managerial expectations for value creation. Most IT departments measure project success based on time, budget, or scope. Only a few have effective processes to assess the business value realized from the projects, (3) Innovation metrics describe the enterprise's ability to pursue potentially valuable opportunities that it would not pursue through its traditional activities. Innovation activities aim to generate a broad set of ideas and help the most valuable ones take shape. Innovation process metrics typically include the breadth of scanning, the extent of employee involvement, and the number and potential benefits of investigated ideas. Other firm-specific innovation metrics include incorporating new technology in the IT infrastructure, enabling new business models, facilitating new product features, and transforming business processes (Mitra et al., 2011).

BA usage is an approach of using third-party analytics tools that take data as input through data-oriented culture. The tool's output is used to analyze and predict using analytical competency. Seddon et al. (2016) developed a model synthesized from the literature to explain how BA usage contributes to business value. Business analytics usage helps make intelligent and smart decisions for day to day working, optimizing in time, cost or resources effort. In the context of IT infrastructure and application management, the impact of BA usage on operational efficiency needs to be tested. Therefore, we frame the following hypothesis:

H4: Higher BA usage will lead to more operational efficiency.

2.5. Speed to Insight

Speed to insight is how quickly the organizations transform raw data into valuable information. Automation, business requirements and reuse are practices that facilitate speed to insight. Data standards and metadata are practices that help organizations automate data on-boarding, integration, and quality processes. Data can be transferred into valuable information faster if the processes are automated. Next, development teams are required to rapidly identify business requirements for data and then translate those requirements into BA products and services. Finally, organizations that invest in reuse can get information into the hands of business users more quickly (Wixom et al., 2013). Speed to insight is required for a firm's expertise in on-premise business intelligence that helps business agility (Mendoza, 2019). Wang and Hajli (2017), in their research on big data analytics in healthcare organizations, found that data analytics was the primary capability followed by the speed to insight as to the next among five different capabilities.

Speed to insight is a continuous improvement of efficiency, productivity and cost through reuse, automation and data standards. Usages of these practices are directly or indirectly related to operational efficiency. Therefore, we frame the following hypothesis:

H5: Higher speed to insight will lead to more operational efficiency.

2.6. Pervasive Use

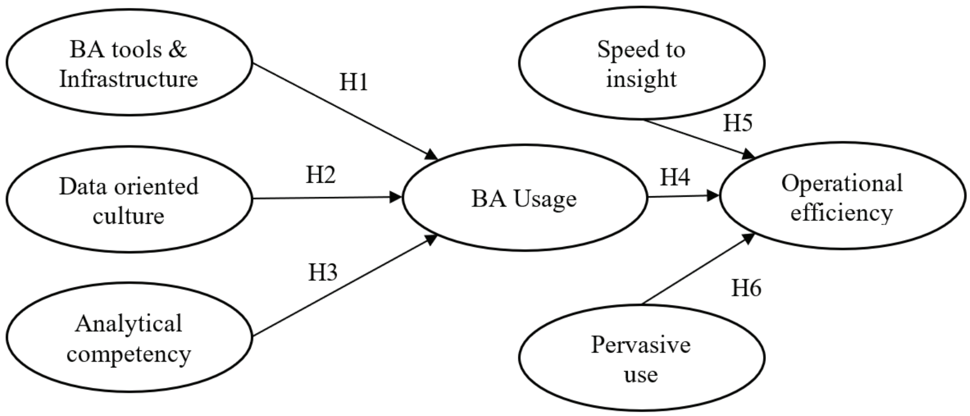
Sustained use of BA is developed through the pervasive use of BA across enterprises. Pervasive use across the organization can be increased by using graphics, mobility of data, and user engagement. As a picture is worth a thousand words, software interfaces that produce visually appealing graphics can lead to business use. Managers can react appropriately using maps, colourful dashboard displays and advanced visualization approaches. Mobile devices like cell phones and tablets can deliver BA, and this mobility leads to the pervasive use of BA. The benefits of mobile BA include more frequent analyses, instant decision-making, more consultative decision-making, and increased self-service and productivity. Finally, organizations can deepen BA usage through practices that promote user engagement, such as self-service, gamification, incentivizing use, collaboration techniques and interactive engagement (Wixom et al., 2013). Pervasive use is to have maximum user involvement in BA usage. It uses techniques like mobility, user engagement and graphics. However, does pervasive use, speed to insight, and BA usage impact operational efficiency? Hence, we frame the following hypothesis:

H6: Higher pervasive use will lead to more operational efficiency.

Ⅲ. Research Methodologies

This study is proposed to test and verify the conceptual model developed through an exhaustive literature review. Data from different organizations in the IT industry are collected to study the influence of BA tools on operational efficiency in the infrastructure domain. This study is quantitative and cross-sectional as the questionnaire responses are collected at one shot and spread over three-four weeks. The survey method collects data on the usage of BA and its influence on operational efficiency in enterprises. A self-administered mailed questionnaire is used as the method for conducting a survey. After participants are selected, an online survey on Google docs is sent to selected participants. Those unable to answer the online survey were shared hard copies of the questionnaire, as many organizations have blocked access to Gmail accounts.

NASSCOM is the apex body of the IT industry in India. The city of Bengaluru is called the IT capital and Silicon Valley of India, contributing 38% of India's total IT exports and having 19% of the total NASSCOM members (NASSCOM, nd). AIMResearch (2021) reported that 30% of the BA business happens



<Figure 1> The Conceptual Model for BA Usage

in Bengaluru. We chose the IT companies in Bengaluru for the study as they represent the IT industry in India.

The survey instrument is developed through an extensive literature review. The seven constructs used in the study are data-oriented culture, analytical competency, BA tools and infrastructure, BA usage, speed to insight, pervasive use and operational efficiency. Mitra et al. (2011) stated that measuring and communicating value provided by IT functions is a big challenge for its CEO. Performance needs are to be measured in operations, projects and innovations. Kiron and Shockley's (2011) references derive items for data-oriented culture, analytical competency, BA tools, and infrastructure constructs. The Wixom et al. (2013) analytics capabilities model is adapted to develop speed to insight and pervasive use items. Burton-Jones and Straub (2006) state that system usage has been long used but have received little theoretical scrutiny, so a detailed empirical study is conducted to understand it. Demography details of the employee like age, experience and size of the company were collected. The draft version of the instrument is validated through subject matter experts, and each item is evaluated on the scale of essential, useful, not essential and not useful. Each item is validated to understand if the general respondent can easily understand and logically answer the questions. A few modifications were done after review.

All the seven constructs of the instrument are developed on the five (5) point Likert scale. The questionnaire is designed in seven sections, each briefing the concept to be measured. The scale options are given a radio button where the respondents are asked to click their option against each item; multiple-choice questions are asked; square tick boxes are provided against each. Table 1 shows the details of the constructs used in instrument development.

Different modes of conducting surveys like electronic email, hardcopy print of instrument and online questionnaire are adapted to implement the survey.

<Table 1> Details of Constructs in Instrument Development

Construct	Sub Construct	No. of Items	Measurement scale	Authors
Data-Oriented Culture	-	15	5-point agreeableness Likert scale	Kiron and Shockley, 2011
Analytical Competency	-	8		
Business Analytics tools and infrastructure	-	8		
Business Analysis Usage	-	8		Burton-Jones and Straub, 2006
Speed to Insight	Reuse	3		Wixom et al., 2013
	Automation	3		
	Data Standards	2		
Pervasive Use	Mobility	3		
	User engagement	3		
	Graphics	2		
Operational Efficiency	-	9		Mitra et al., 2011

Total responses received from an online survey on Google docs was 36, while responses from the hard copy of the questionnaire received were 180. Thus, the total number of respondents who answered this survey was 216. During the process of coding and editing, four (4) responses were found to be incomplete with ambiguity in data, so they were dropped and not considered for analysis. After removing four (4) responses, only 212 were taken for statistical analysis. IBM – SPSS (Statistical Package for the social science) and VPLS (Partial least squares Regression) were used for data analysis.

Ⅳ. Data Analysis and Results

4.1. Descriptive Statistics

First, the descriptive statistics of the demography of the respondents is presented. Out of the total respondents (212), 43.2% (92) have experienced between 11 years to 15 years, while 25.4% (54) of respondents' experience is between 6 years to 10 years. 12.2% (26) of respondents have a maximum of five (5) years of experience, while 18.8% (40) respondents have experience between 16 years to 20 years. 77.5% (165) are males among the responses collected, while 22.1% (47) respondents are females. Analysis of the respondent's age groups highlighted that 36.2% (77) respondents are between 31 years to 35 years. Respondents in the age group of 36 years to 40 years are 32.9% (70), while 22.5% (48) respondents in the age group of 26 years to 30 years. The remaining 8% (17) are below the age of 25 years. An outlier test is conducted using the Box plot. Six (6) cases are removed as outliers from the total sample size (212), and finally, only 206 responses are considered inferential analysis.

4.2. Reliability and Validity

We further check the validity of the constructs using Average Variance Extracted (AVE) and the reliability using Composite Reliability (CR) and Cronbach's alpha. The results are presented in Table 2. The value of Cronbach alpha > 0.7 indicates satisfactory internal consistency reliability. The result shows that the Cronbach alpha is above 0.7 for all the constructs.

The values of CR for all the constructs are above the threshold level of 0.7, ensuring the constructs' reliability. The AVE values are greater than 0.5 and

<Table 2> Reliability and Validity Statistics

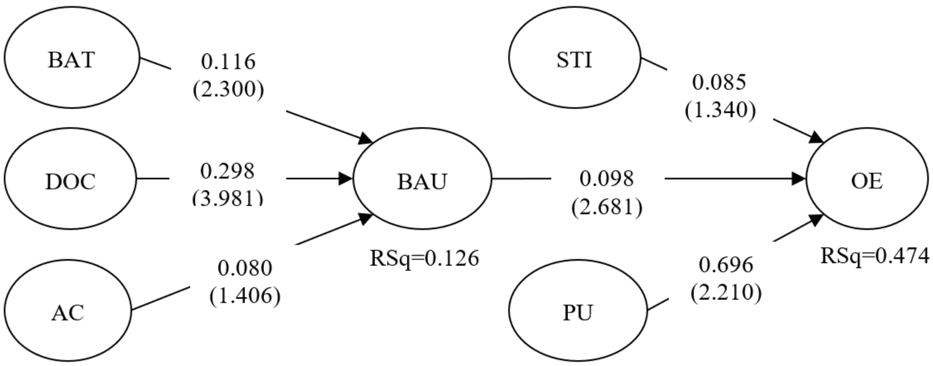
	CR	AVE	Alpha	DOC	AC	BAT	BAU	STI	PU	OE
DOC	0.794	0.617	0.747	***0.785***						
AC	0.835	0.632	0.902	0.207	***0.795***					
BAT	0.916	0.685	0.897	0.247	0.421	***0.827***				
BAU	0.791	0.658	0.709	0.317	0.202	0.332	***0.811***			
STI	0.913	0.727	0.900	0.350	0.375	0.458	0.358	***0.852***		
PU	0.937	0.881	0.855	0.480	0.393	0.374	0.401	0.485	***0.938***	
OE	0.840	0.725	0.739	0.314	0.430	0.372	0.407	0.416	0.522	***0.851***

Note: Values in the diagonal are the Square root of AVE. DOC = Data-oriented culture, AC = Analytical competence, BAT = Business Analytics tools and infrastructure, BAU = Business Analysis Usage, STI = Speed to Insight, PU = Pervasive Use, OE = Operational Efficiency lower than the CR, showing a good convergent validity. With the Square root of AVE values being higher than the correlation of the construct to all the other constructs, discriminant validity is achieved (Gefen and Straub, 2005).

4.3. Partial Least Squares Regression

PLS path analysis is used to investigate the simultaneous effect of the independent variables on the dependent variable. PLS regression is particularly suited when the matrix of predictors has more variables than observations and multicollinearity among values. <Figure 2> shows the path analysis for the conceptual model. BA usage (BAU), RSq value is 0.126. It can be inferred that variables, data-oriented culture (DOC), BA tools and infrastructure (BAT) and analytical competency (AC) explain the variation in BA usage (BAU) to the extent of 12.6%. The operational efficiency (OE) RSq value is 0.474. It can be inferred that variables BA usage (BAU), speed to insight (STI) and pervasive use (PU), explain the variation in operational efficiency (OE) to the extent of 47.4%.

<Table 3> shows the estimates of the path from the structural model. The value of t above 2 is acceptable for validating the influence of the independent variable on the dependent variable. Data-oriented culture (DOC, B = 0.298, t = 3.981) and BA tools and infrastructure (BAT, B = 0.116, t = 2.30) influences BA usage (BAU). Hence hypotheses H1 and H2 are accepted. Analytical competency (AC, B = 0.080, t = 1.406) has less influence on BA usage and is not significant; hence hypothesis H3 is rejected. BA



<Figure 2> Path Analysis Diagram

<Table 3> Structural Model

Independent and dependent variables	Estimate value (B)	t-value
DOC -> BAU	0.298	3.981
BAT -> BAU	0.116	2.300
AC -> BAU	0.080	1.406
BAU -> OE	0.098	2.681
STI -> OE	0.085	1.340
PU -> OE	0.696	2.210

usage (BAU, B = 0.098, t = 2.681) and pervasive use (PU, B = 0.696, t = 2.210) influences the operational efficiency. Hence hypotheses H4 and H6 are accepted. Speed to insight (STI, B = 0.085, t = 1.68) has less influence on operational efficiency and is not significant. Therefore, hypothesis H5 is rejected.

Ⅴ. Discussions

This study investigated the influence of BA usage, speed to insight, and pervasive use on operational efficiency in IT infrastructure and application management. BA usage is used in measuring the frequency and duration of BA tools usage. Operational efficiency is used at the organizational level to measure business performance and continuously enhance operational parameters. BA usage has a significant influence on operational efficiency. This study shows that costs of operation, equipment idle time, manpower utilization are factored for analyzing the performance of individuals or departments in many organizations. Many organizations have agreed to use these parameters for measuring progress and status. Mitra et al. (2011) have revealed the CIO's challenges in analyzing the organization's performance. He recommends nine types of metrics varying in scope and performances they measure based on his study. He suggests using IT operation, internal process support, and project delivery to measure information technology performance.

Results of the study show details like the number of tickets reopened and tickets resolved are tracked at individual and department levels to gauge the status independently and along with competitors in the same domain. Many respondents agreed that gauging performance on these parameters increases tasks' efficiency and execution. Dines (2011) outlined the technical metrics used for measuring the performance in the infrastructure operations domain. He discusses the parameters used in daily working and then deployed for measuring performances.

Performance measurement at the root level leads to improvement in leading layers above and eventually leads to enhancement or growth of results. It also helps analyze the gap areas for improvements and utilize strengths better. Organizations are reaping the benefits of BA. However, usage is still at the micro-level, which would help prevent revenue leakage and business deals if used properly and proactively. Though the influence is very minimal, more usage of BA will increase operational efficiency.

This study proposed the influence of speed to insight and pervasive use on operational efficiency in IT infrastructure and application management. Speed to insight is about how organizations transform raw information into usable information expeditiously. At the same time, Pervasive use is the comfort and ease with which an individual can adopt analytics for application. The study highlights the use and application of slice and dice formatting, automation of MIS, reduced downtime of applications and servers, and online information, all expediting the usage of raw and processed data. Mobile application is being used in organizations for easy and faster access. These are user-friendly with a colourful display having interfaces with many other departments. Respondents also agreed to an increase in customer satisfaction after its usage.

Some previous studies and the current study found the implications of small actions like automation, reusability and putting data standards in place. Along with business usage, these actions help improve operational efficiency, which is always measured at the organization level to analyze the performance. Different departments should be mandated to use it for their daily report generation and status sharing. Organizations can further improve their usage by placing these checks as a part of employee performance analysis, which will enable many leaks from escaping at the individual level and make them also accountable and responsible for the result.

It is highlighted through the study that data-oriented culture and BA tools and infrastructure have a significant influence on BA usage in organizations. Analytical competency alone does not significantly influence BA usage. It is found through observation that analytical competency skills are being used in organizations. Still, they are not aware that they are using analytical skills. Employees need to be trained and upgraded with the technical skills needed to understand this skill. Data-oriented culture is widely practised across the business units, making automatic data collection and analysis part and parcel of daily work activities in offices. Using third party BA tools and infrastructure is currently a big ongoing drive in the organization. Different analytical tools are examined and verified to understand which tool to deploy according to business needs.

Thus, the objective to investigate the influence of data-oriented culture, BA tools and infrastructure, and analytical competency on the usage of BA in IT infrastructure and application domain is validated. Analytical competency, data-oriented culture, BA tools, and infrastructure can influence BA usage. However, when analytical competency is used in isolation, it does not influence BA usage.

This study discusses the influence of BA usage, speed to insight and pervasive use on operational efficiency. It is proposed that BA usage and pervasive use significantly influence operational efficiency in IT infrastructure and application management domain. However, speed to insight does not significantly influence operational efficiency. It has been suggested that respondents are unaware of speed to insight, and analytics tool deployment is at a very initial level in organizations, so adequate process, standards and automation processes are still not in place to maximize its reuse capability. This study found that organizations can promote BA on mobile phones and many other electronic portable devices due to technology advancement and ease of use. Respondents are attracted to the user-friendly features and faster access features of the devices.

Thus, the objective 'To investigate the influence of BA usage, speed to insight and pervasive use on the operational efficiency of IT infrastructure and application domain.' is validated that speed to insight, pervasive use, and BA usage influence operational efficiency when used together. Though the awareness in organizations is at a very initial level for speed to insight and pervasive use, influence is low on operational efficiency.

5.1. Implications of Findings

This study indicates that BA usage directly influences operational efficiency in its infrastructure and application domain along with the practice of pervasive use. Though practices like data standards, reuse and automation are used by organizations at a preliminary level, they still have less influence on efficiency. Practices of reuse and automation should be encouraged in the infrastructure domain. Thus, it is critical that analytics training and usage be continuously improved and simplified. Implications offered from this study are mentioned below.

Data-oriented culture influences BA usage, and managers use structured and unstructured data to make strategic decisions. Daily zeta bytes of data are collected for understanding the leads, which enable organizations to know their problem areas and work towards improving them while at the same time smartly using their strengths for better positioning in business growth. No more decisions are based on past experiences and intuitions only. Competitor data is also strategically analyzed for better and smarter decisions.

BA tools and infrastructure have a significant influence on BA usage. Analytics was earlier used on MS Excel in organizations, but current analytics tools can work in collaborative real-time. Data from multiple sources in multiple formats can easily be correlated. Dynamic processing can empower users to make smarter decisions and save time and cost by reducing redundant tasks.

BA influences operational efficiency, indicating that efficiency will improve when data-oriented culture, analytical competency, and business tools and infrastructure are deployed and practised. Efficient processes in place lead to an improvement in overall efficiency. Thus, BA usage will increase if practices like data-oriented culture, analytical competency, and BA tools and Infrastructure usage are practised correctly. BA usage, pervasive use and speed to insight influence operational efficiency. Thus, an increase in BA usage and pervasive use and speed to insight will increase operational efficiency.

Pervasive use has a significant influence on the operational efficiency of the business. Pervasive use can be achieved through mobility, user interfaces and graphics. Organizations are promoting easy and faster means for using BA tools. Thus, high-end technology and graphics encourage users to use them comfortably. Speed to insight enables organizations to use practices like reuse, automation and data standards, and analytics tools for better results. BA is slowly gaining acceptance in organizations; hence actual results of BA usage will take some time. Practices like reuse and automation are still not practised. Thus, employees should be encouraged and enabled for more and more usage of the analytics tool.

Ⅵ. Conclusion

This study is conducted to understand the influence of BAusage and pervasive use and speed to insight operational efficiency in its infrastructure and application domain. Parameters like the presence of data-oriented culture, usage of analytical competency and availability of BA tools and infrastructure are analyzed to understand their influence on BA usage. The study contributes to a model to predict different factors influencing BA in enterprises. This study enables enterprises to focus on individual core strengths and gain benefits from them while at the same time knowing the self-weakness and working towards it. This study also enforces organizations in the same or different domains to understand the benefits and challenges of BA. Usage of BA to analyze operational efficiency is a new and upcoming area in the IT infrastructure and application domain. As very little research has been conducted in IT Infrastructure and application domain, this study will help many other researchers take this study as a base reference and conduct more studies in a more diverse environment.

This study is limited to the IT infrastructure and application domain only, though various other functions across IT organizations use BA. The study was conducted in the infrastructure domain using BA, but very few enterprises use it in capacity mode. The other limitation of this study was the awareness level among employees. However, they use some tools of Business Analytics but are not aware of it. In addition, a very small team size working on Analytics was another major challenge, as it was difficult to get leads of them and get an adequate response because of their resistance to sharing information.

The successful validation of the conceptual model in the IT infrastructure and application domain recommends further replication and validation in various industries. Research can be conducted in other domains in Information technology, i.e., retail, banking, healthcare, manufacturing, transportation, entertainment, and the aviation domain other than Infrastructure application and management to explore their BA usages and benefits derived. The benefits derived from the usage of BA are well known from literature and the conceptual model. This study can be extended by collecting data from two or three large enterprises using BA and then comparing them to understand better which company is using the business tools. Each company's major objectives and benefits are derived after using analytics.

The key success factor of analytics implementation in any organization depends on senior executives' drive. Making decisions based on data, facts, and complex statistics doesn't help unless they make substantial changes in behaviour and culture driven from the top hierarchy layer. Business leaders have to be supporters but have to become cheerleaders for executives. Analytics have to be used in multiple functional areas using sophisticated statistical analysis and predictive modelling. This study has highlighted that deploying analytical tools does not help the company. Data-oriented culture and analytical competency need to be developed to increase analytics usage. Developing a data-oriented culture and analytical skills cannot be developed overnight, but it takes several months or years. Assembling the right data at the right time and by the right person will only enable the next step of finding or analyzing the data with the right tools. The exact relationships can only be established when employees and culture become regular. The culture of the enterprises has to shift from a traditional working style to data, statistics and domain knowledge. The future of the IT infrastructure and application management domain lies not in technology but in deriving the correct and meaningful information from the huge piles of data collected by the organizations.

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<Appendix> Descriptive Statistics of Test Variables

Variables	Mean	SD		Variables	Mean	SD
Data-Oriented Culture				Business Analytics Tools and Infrastructure		
Decisions based on data	4.25	0.780		ETL	3.75	0.871
Access to Data	3.59	0.906		Data warehouse	3.87	0.891
Key performance	3.84	0.918		DBMS	3.84	0.899
Transparency	3.82	0.962		Text Analysis	3.74	0.889
Digital format	3.84	0.954		Statistical Analysis	3.78	0.838
Enough Data	3.93	0.868		Predictive Analysis	3.52	0.889
Management support	3.82	1.030		MIS Needs	3.71	0.865
Transfer of Data	3.74	1.091		Model Management	3.81	0.904
Strong data governance	3.86	0.876		Business Analytics Usage		
Good Data management	3.81	0.884		BA Frequently	3.35	1.058
Right and Current Info	3.82	0.963		Generate Reports	3.34	1.152
Data Standards	3.98	0.944		Access records	3.31	1.079
Info available	3.93	0.887		Operate BA	3.14	1.143
Shadow system	3.74	0.896		Menu Options	3.21	1.151
Automation	3.79	1.100		Features in BA	3.27	1.160
Analytical Competency				Business Application	3.70	1.031
Resources	3.82	1.039		Strategic decision making	3.70	0.956
Collaborative systems	3.99	0.946		Speed to Insight		
Functional channels	3.89	0.940		Centralized	3.84	0.831
Data integration	3.91	0.939		Catalogues	3.74	0.769
Focused skills	4.00	0.879		Slice – dice format	3.63	0.783
Analytical skills	4.12	0.900		Service Delivery	3.56	0.882
Hire people	3.85	0.883		Automated MIS Report	3.51	0.873
Spreadsheets use	3.82	0.962		Online Information	3.51	0.941
Operational Efficiency				Customer Satisfaction	3.57	0.944
Asset Efficiency	4.42	0.629		Reduced downtime	3.83	0.920
Speed of Tasks	4.29	0.623		Pervasive Use		
Human Errors	4.30	0.737		Dashboard Display	3.72	0.863
Cost of Operation	4.25	0.790		Maps and Graphs	3.74	0.840
Hardware Utilization	4.16	0.754		Interfaces	3.26	0.966
Equipment downtime	4.07	0.934		Mobile phones	3.28	1.085
Equipment idle time	4.11	0.810		Easily Accessible	3.39	1.036
Manpower Utilization	4.24	0.756		Easy to use	3.17	1.030
Number of tickets	4.00	0.913		Faster	3.26	1.033
				Reports wizard	3.58	0.996

<Appendix> Questionnaire

SURVEY ON BUSINESS ANALYTICS USAGE Questionnaire Against each statement given below, please select the appropriate option on a scale of "To a large extent" to "Not at all" to indicate to what extent the statement reflect your organizational practice.

Data-Oriented Culture: Data-oriented culture is about organizational level standard measure criteria and to collect data centrally.		To a large Extent	To a Moderate Extent	To some Extent	To little Extent	Not at all
1	Decisions in the organization are based and supported by data	❍	❍	❍	❍	❍
2	I have access to data required to take decisions	❍	❍	❍	❍	❍
3	Key performance indicators are used to measure performance outside SLA	❍	❍	❍	❍	❍
4	There is transparency of information across the organization (role based)	❍	❍	❍	❍	❍
5	Documents are available in digital format	❍	❍	❍	❍	❍
6	1 have enough data that are required to my job effectively	❍	❍	❍	❍	❍
7	Management supports the data capturing, storing and utilizing the data.	❍	❍	❍	❍	❍
8	Transferring of data in digital format is encouraged in our organization	❍	❍	❍	❍	❍
9	There is strong data governance to manage data	❍	❍	❍	❍	❍
10	Good data management practices are followed	❍	❍	❍	❍	❍
11	Right and current information is available	❍	❍	❍	❍	❍
12	Definite data standards in place for operational process measurement (i.e., Incident management, Problem management, Change management)	❍	❍	❍	❍	❍
13	Information is available to those who require it	❍	❍	❍	❍	❍
14	Shadow system for data transformation to central system (a staging system to ensure good quality of data is going to production central system)	❍	❍	❍	❍	❍
15	The automated practice of collecting data centrally in predefined standard format for all the critical processes and services.	❍	❍	❍	❍	❍

Availability of BA Tools and Applications: Business Analytics tools helps to enable and facilitate in making intelligent decisions in collaboration from different sources.		To a large Extent	To a Moderate Extent	To some Extent	To little Extent	Not at all
16	Extract, transform, load (ETL) tools are available	❍	❍	❍	❍	❍
17	Data warehouse infrastructure and capability is available	❍	❍	❍	❍	❍
18	Infrastructure for DBMS (multiple types)	❍	❍	❍	❍	❍
19	Tools and skills available for Text analysis	❍	❍	❍	❍	❍
20	Tools and skills available for Statistical analysis	❍	❍	❍	❍	❍
21	Skills available for Modelling and predictive analytics	❍	❍	❍	❍	❍
22	Tools for Reporting and Visualization usage for MIS needs	❍	❍	❍	❍	❍
23	Software and model management tools	❍	❍	❍	❍	❍

<Appendix> Questionnaire (Cont.)

Analytical Competence: Analytical competence is a specialized line of business or functionality focused approach to analytics, such as deepening analytic skills within operations, finance or marketing to optimize and predict specific business processes.		Strongly Agree	Agree	Neutral	Dis-agree	Strongly Disagree
24	Our organization has people who can work on an Enterprise-wide information platform	❍	❍	❍	❍	❍
25	Our organization has people who can work on collaborative systems	❍	❍	❍	❍	❍
26	We have a system that shares data across functional channels	❍	❍	❍	❍	❍
27	There are data integration practices in place and skills	❍	❍	❍	❍	❍
28	People in the departments have good functionally focused skills	❍	❍	❍	❍	❍
29	Our organization has people who have good analytical skills	❍	❍	❍	❍	❍
30	Our organization has people who have good analytical skills	❍	❍	❍	❍	❍
31	Our organization has most people who can use spreadsheets and visualization effectively	❍	❍	❍	❍	❍

BA Usage: BA usage is used in measuring the frequency and duration of usage of business analytics tools.		To a large Extent	To a Moderate Extent	To some Extent	To little Extent	Not at all
32	I use the BA frequently in my job	❍	❍	❍	❍	❍
33	I generate reports in BA system	❍	❍	❍	❍	❍
34	I access records in the BA system	❍	❍	❍	❍	❍
35	I am aware of the various menus available in the BA system	❍	❍	❍	❍	❍
36	I have used the features available in the BA system	❍	❍	❍	❍	❍
37	I have used the BA system for the business application	❍	❍	❍	❍	❍
38	Our firm has used BA for strategic decision making within and across the enterprise.	❍	❍	❍	❍	❍
39	Our firm has used BA for providing better insight of organizational data resources.	❍	❍	❍	❍	❍

40	Which of these statements best describes the state of BA in your company?	❍ We're just getting started ❍ **Departmental BA**: BA is used by one or a few departments with no coordination of projects or integration of data across departments ❍ **Partially coordinated BA:** BA is used by multiple departments, with some informal project coordination and sharing of data ❍ **Enterprise BA:** BA is managed as an integrated program of projects, all supported by an enterprise data warehouse
41	Which of these statements describes the CURRENT use of business analytics in your company? (Select all that apply)	☐ Traditional reporting, but using newer/better technology ☐ Analytical tool for analysts and power users ☐ Self-service mechanism to make information available to a broad audience ☐ Monitoring system that helps management "keep a finger on the pulse" of the business ☐ Mission-critical system that drives processes and profits Strategic system that provides a competitive advantage ☐ Don't know or no perspective ☐ Other (please specify)

<Appendix> Questionnaire (Cont.)

42	Which of these types of information delivery and presentation (sometimes called "styles of BA") are available to you, and which do you personally use? (Select all that apply)	☐ Traditional reporting ☐ Charts and graphs ☐ Scorecards and dashboards ☐ OLAP (slice and dice) ☐ Advanced analytics (regression, collaborative filtering, data mining, etc.) ☐ Predictive analytics (statistical forecasting, credit scoring, etc.) ☐ Activity/event monitoring and alerts

Effective Use of BA (Speed of Insight and Pervasive Use): Speed to insight is concerned with how expeditiously organizations transform raw data into usable information. Companies can increase the use of business analytics by adopting practices that encourage more pervasive use of business analytics across the enterprise		To a large Extent	To a Moderate Extent	To some Extent	To little Extent	Not at all
43	We utilize centralized stored data to provide Data as a Service (DaaS) to internal and external customers	❍	❍	❍	❍	❍
44	We use catalogues of best practices for designing dashboards to meet various objectives (critical parameters tracking, service improvement themes etc.)	❍	❍	❍	❍	❍
45	We have parameterized/dynamic slice-dicing reporting formats	❍	❍	❍	❍	❍
46	The dashboard displays are colourful and interactive	❍	❍	❍	❍	❍
47	Maps, graphs and illustrations are used in the interface screens	❍	❍	❍	❍	❍
48	The interfaces use animated graphics	❍	❍	❍	❍	❍
49	Most BA applications are available on mobile phones and tablets	❍	❍	❍	❍	❍
50	BA applications can be easily accessed from anywhere	❍	❍	❍	❍	❍
51	BA are easy to use on mobile devices.	❍	❍	❍	❍	❍
52	Using BA applications on mobile devices are faster	❍	❍	❍	❍	❍
53	Reports wizards are available for easy use	❍	❍	❍	❍	❍
54	We use MIS and online information in our practice for service delivery reviews.	❍	❍	❍	❍	❍
55	We have automated MIS reporting no dedicated support for MIS requirements.	❍	❍	❍	❍	❍
56	We use MIS and online information in our practice for service delivery reviews.	❍	❍	❍	❍	❍
57	Service level tracking and customer satisfaction has improved	❍	❍	❍	❍	❍
58	Using analytics inputs, we are able to reduce downtime of services	❍	❍	❍	❍	❍

Operational efficiency: Operational efficiency is used at the organizational level to measure business performance and continuously enhance operational parameters.		Very Much Improved	Minimally Improved	No Change	Minimally Decreased	Very Much Decreased
59	Our asset efficiency (faster services, reduced downtime, improved/optimum utilization) has	❍	❍	❍	❍	❍
60	Speed of the tasks has (BA inputs to task automation & best utilization of knowledge base)	❍	❍	❍	❍	❍
61	Human error and manual activity (BA inputs to fix issues caused by human errors) has	❍	❍	❍	❍	❍

<Appendix> Questionnaire (Cont.)

62	Cost of operation (total cost of ownership) has	❍	❍	❍	❍	❍
63	Deployed Hardware Utilization Efficiency (BA inputs for asset consolidation leads to better utilization) has	❍	❍	❍	❍	❍
64	Equipment downtime (Critical Asset health) has	❍	❍	❍	❍	❍
65	Equipment idle time (average idle time of data centre CIs, BA inputs for consolidation) has	❍	❍	❍	❍	❍
66	Manpower utilization (workload management within the support group) has	❍	❍	❍	❍	❍
67	Number of tickets (Incidents, service requests) has	❍	❍	❍	❍	❍

Employee details

1	Gender:	❍ Male	❍ Female		
2	Age (Years)	❍ 20-25	❍ 26-30	❍ 31-35	❍ 36-40
3	Experience (Years):	❍ 0-5	❍ 6-10	❍ 11-15	❍ 16-20
4	Size of the Company: (No. of Employees)	❍ <1000	❍ 1001-3000	❍ 3001-5000	❍ Above 5000
5	Designation:	❍ Manager	❍ Senior Manager	❍ Consultant	❍ Architect

Any additional information or comments   Thank you for spending your valuable time

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