Asia Pacific Journal of Information Systems
Vol. 30 No. 2 (June 2020), 397-419

ISSN 2288-5404 (Print) / ISSN 2288-6818 (Online)
https://doi.org/10.14329/apjis.2020.30.2.397

Key Themes for Multi-Stage Business Analytics Adoption in Organizations

Amit Kumar[a,*], Bala Krishnamoorthy[b], Divakar B Kamath[c]

[a] *Doctoral Candidate, NMIMS, School of Business Management, Mumbai, India*
[b] *Professor, NMIMS, School of Business Management, Mumbai, India*
[c] *Director, Google Cloud, Mumbai, India*

A B S T R A C T

Business analytics is a management tool for achieving significant business performance improvements. Many organizations fail to or only partially achieve their business objectives and goals from business analytics. Business analytics adoption is a multi-stage complex activity consisting of evaluation, adoption, and assimilation stages. Several research papers have been published in the field of business analytics, but the research on multi-stage BA adoption is fewer in number. This study contributes to the scant literature on the multi-stage adoption model by identifying the critical themes for evaluation, adoption, and assimilation stages of business analytics. This study uses the thematic content analysis of peer-reviewed published academic papers as a research technique to explore the key themes of business analytics adoption. This study links the critical themes with the popular theoretical foundations: Resource-Based View (RBV), Dynamic Capabilities, Diffusion of Innovations, and Technology-Organizational-Environmental (TOE) framework. The study identifies twelve major factors categorized into three key themes: organizational characteristics, innovation characteristics, and environmental characteristics. The main organizational factors are top management support, organization data environment, centralized analytics structure, perceived cost, employee skills, and data-based decision making culture. The major innovation characteristics are perceived benefits, complexity, and compatibility, and information technology assets. The environmental factors influencing BA adoption stages are competition and industry pressure. A conceptual framework for the multi-stage BA adoption model is proposed in this study. The findings of this study can assist the practicing managers in developing a stage-wise operational strategy for business analytics adoption. Future research can also attempt to validate the conceptual model proposed in this study.

Keywords: Business Analytics, Dynamic Capabilities, Resource-Based View, Technology Adoption, Toe Framework, Diffusion of Innovation

Ⅰ. Introduction

Business analytics (BA) helps in understanding customer insights, improve decision making, and automate business processes in organizations (Davenport, 2006; Sharma et al., 2014; Watson and Wixom, 2007).

*Corresponding Author. E-mail: amitsinha.in@gmail.com

Organizations are adopting analytics to generate customer insights, improve customer experience, customize products and offers, automate business processes for enhancing a firm's performance and develop a competitive advantage (Barton and Court, 2012; Kumar and Petersen, 2005). Organizations using advanced BA can transform their analytical capabilities into a strategic position (Akter et al., 2016; McAfee et al., 2012). However, many organizations fail to derive strategic benefits from BA adoption (Klatt et al., 2011). As per a report entitled "Big Data and Executive Survey 2019" published by industry consultants New Vantage Partners, at least 77.1% of the senior executives reported adoption of business analytics as a challenge. In a study, it was found that only three out of sixteen firms had applied BA for making strategic decisions, and that was limited to few areas of business operations (Coghlan et al., 2010). The investments in the adoption of BA have increased in firms, but the development of successful BA adoption is a challenge for many firms (Bean and Davenport, 2019).

Business analytics has attracted a significant amount of interest over the last decade in academic research and industry. A number of these studies have focused on the understanding of BA, adoption of BA, and its impact on business performances (Akter et al., 2016; Chen at al., 2012; Gandomi and Haider, 2015; Lavalle et al., 2011). Some studies have discussed the reasons for firms failing in the adoption of BA. As per Ransbotham et al. (2014), the gaps between organizations' capability to produce analytics and the manager's interpretation of the analytical results for their decision making limits the effectiveness of BA adoption. Bose (2009) highlighted organizational support, implementation of advanced analytics, regulatory environment and data privacy, technology skill gaps, and availability of data across organizations as the significant challenges in BA adoption. Banerjee and Williams (2009) found the lack of analytical skills among the domain employees and lack of domain knowledge among the analytics professionals as a barrier in achieving analytical capability. These studies have contributed to the development of proper understanding about the importance of BA, the impact of BA, and the enablers and challenges of BA adoption. Still, there is a considerable need to understand BA adoption from the perspectives of multiple stages of BA adoption, theoretical perspectives, and research methodologies.

As per Rogers (1995), there are different stages of technology adoption, and technology adoption is an evolutionary process. BA adoption is a technology adoption, and it follows an evolutionary adoption process. Many of the studies have limited the BA adoption study to the stages of evaluating the BA, the decision to adopt BA, and its implementation process (Corte-Real et al., 2014). There is less research available on the usage of BA in organizational activities. The primary research gap is the lack of sufficient studies on understanding the diffusion process in the adoption of BA, as this is a multi-stage adoption process (Nam et al., 2019). There is a need to identify the critical success factors influencing BA adoption into multiple stages. The second research gap identified is the fragmentation of theoretical perspectives as the base for studying BA adoption (Al-Qirim et al., 2019; Frizzo-Barker et al., 2016). Academic papers have studied the adoption of technology adoption using different theoretical perspectives. However, no such study has been conducted that attempts to explore the various stages of BA adoption using different theoretical models. This study integrates the two research gaps and addresses specific research questions.

1. *What are the different stages of the BA adoption process in firms?*
2. *What are the significant factors that influence the different stages of BA adoption?*

The main objectives of this paper are to contribute to the discussion and relevance of multi-stage BA adoption and to develop an integrated theoretical model based on the analysis of factors influencing BA adoption at multiple stages. This study contributes to the academic research by mapping the elements with numerous stages of BA adoption. This study can aid future research studies invalidation of different adoption stages such as adoption, implementation, and use of BA. This study also provides a multi-theory base for validating BA adoption for future research. The main theoretical perspectives used in this study are (RBV) Resource-Based View (Wernerfelt, 1984); Dynamic Capabilities (Teece et al., 1997); Diffusion of Innovations (Rogers, 1995), and Technological, organizational and environmental (TOE) framework (Tornatzky and Fleischer, 1990). The theoretical lenses used in this study explore innovation diffusion from the perspective of resources and capabilities, organizational, technological, and environmental perspectives. The findings of this study are linked with the popular theoretical perspectives for studying technology adoption. In the context of technology adoption studies, no one theory can sufficiently explain the adoption of different technology innovations (Ramdani and Kawalek, 2008; Wang et al., 2010). Hence, this study attempts to be more comprehensive in identifying the themes for BA adoption. This is the first study that attempts to map the factors for BA adoption stages using thematic content analysis. Some of the studies that have validated BA adoption stages are empirical studies (Nam et al., 2019; Puklavec, 2018). This study also has practical contributions as this paper presents the essential guidelines that can be practiced by firms for focusing on the enablers and challenges in the BA adoption process.

This paper is structured into the following sections: literature review, research methodology, data analysis and findings, discussion, conclusion, implications, and limitations of the study.

Ⅱ. Theoretical Background

2.1. Business Analytics Adoption Stages

This section discusses the research conducted in the field of BA adoption. Many research papers have studied the adoption of BA in organizations and explored the factors influencing BA adoption. A significant number of studies have explained the factors influencing the decision to adopt BA in organization. We have also reviewed articles on technology adoption stages, as BA adoption is considered a technology adoption. As per Lind and Zmud (1991), business analytics is technology innovation, as the operational idea of BA is based on technology.

BA adoption is the organization's decision to use business analytics technology (Chen et al., 2015; Oliveira et al., 2014). The adoption of BA can be separated into multiple stages. According to Corte-Real et al. (2014), the different stages of BA adoption are adoption, implementation, use, and impacts of use. Puklavec et al. (2018) described three stages of BA adoption: evaluation of BA, adoption of BA, and the use of BA in the value chain activities of the organization. Bose and Luo (2011) discussed the adoption process of green technology into three stages: initialization, integration, and maturation. In the initialization stage, the organization in the process of adopting technology evaluates the technology. In the integration stage, the organization, over time, learns more about the technology and develops new applications to integrate with the technology. The maturation stage of technology adoption is when the integration of technology into the organization's value chain activities is complete and routinized. Chong and Chan (2012) studied the adoption of Radio Frequency Identification (RFID) into three adoption stages: evaluation, adoption, and routinization. Chan and Chong (2013) also discussed the adoption of mobile based supply chain management into three different stages: evaluation, adoption, and routinization. Nam et al. (2019) described the BA adoption stages as initiation, adoption, and assimilation. Kim and Garrison (2010) described the adoption of RFID into the stages of evaluating the RFID technology, adoption of technology, and integration of technology with value chain activities. Zhu et al. (2006) studied the adoption of E-business into the stages of usage and impact of E-business.

Gunasekaran et al. (2017) in their study conceptualized big data and predictive analytics adoption processes as three stages: acceptance, routinization, and assimilation. Nam et al. (2019), in a more recent study, suggests the different stages of BA adoption are: initiation, adoption of BA, and finally, assimilation of BA. The initiation stage is the evaluation of BA. The adoption stage is the usage of BA in decision making. As per Nam et al. (2019), the assimilation stage of technology adoption is the more advanced stage than routinization. According to Nam et al. (2019), in the assimilation stage, the technology is integrated across different work units, and it can also lead to improved activities performance over the competitors. Liang et al. (2007) had also studied the assimilation of an enterprise system in organizations.

The initiation and adoption of BA have been considerably studied, but the literature on the assimilation stage is scant. In this study, we have attempted to address all the three stages of technology adoption. Next, we develop the three adoption stages of BA. In this study, we have described the adoption of BA into three stages: evaluation of BA, usage of BA, and the assimilation of BA.

2.1.1. BA Evaluation Stage

The evaluation stage of technology adoption is the identification of the organization's needs and the organization's search to find technological innovations that can solve the organization's problems (Rogers, 1995). The extent to which BA can be useful for solving a problem will influence the evaluation of BA adoption (Alshamaila et al., 2013; Esteves and Curto, 2013; Ka and Kim, 2014; Verma and Bhattacharyya, 2017). We have reviewed the factors influencing the BA evaluation stage in organizations.

The decision to adopt any technology innovation is determined by the perceived benefits of innovation among the top managers (Subramanian and Nosek, 2001). Many studies suggest that organizations often consider the business value of BA adoption as a significant factor (Chen and Nath, 2018; Low et al., 2011; Nkhoma and Dang, 2013; Premkumar et al., 1994).

A lot of studies suggest the Top Management Support (TMS) as a critical factor in the evaluation stage of BA adoption (Chan and Chong, 2013; Gangwar, 2018; Jeyaraj et al., 2006; Ramanathan et al., 2017; Sun et al., 2018). The top management support initiates the BA adoption stage and helps in formulating the vision for the adoption of BA (Puklavec et al., 2018). There is strong support for TMS as a significant factor influencing BA adoption at the evaluation stage.

The Organization Data Environment (ODE) for BA adoption has a significant and positive influence on the evaluation stage in BA adoption (Nam et al., 2019; Popovič et al., 2012; Ramamurthy et al., 2008; Verma and Bhattacharyya, 2017). The availability of quality data, data accessibility, and well-defined data rules for the collection, storage, and analysis of data are critical to developing an ODE (Ghasemaghaei et al., 2018).

The organizational decision-making structure has also been studied as a factor by some of the studies. For example, Nam et al. (2019) found the centralized analytics function can negatively influence the decision to evaluate new BA projects. As per Grossman and Siegel (2014), the organizations with a decentralized analytics function are more likely to assess and search new BA technologies than the centralized analytics function.

The data-driven decision making culture is a significant factor influencing the evaluation of BA adoption in organizations. A number of studies have discussed the positive influence of organization data culture on BA evaluation (Kiron and Shockley, 2011; Sun et al., 2018; Verma and Bhattacharyya, 2017).

Few studies have found the perceived cost of BA adoption as a factor influencing the evaluation stage of BA adoption (Alshamaila et al., 2013; Gutierrez et al., 2015; Verma and Bhattacharyya, 2017). The cost of BA adoption is an inhibitor than enablers (Verma and Bhattacharyya, 2017). However, the results for factors influencing the evaluation stage of BA adoption are contrasting. As per Puklavec et al. (2018), the perceived cost of adoption of BA is non-significant factors influencing BA adoption. A plausible reason is that the cost of technology has become less due to the availability of many open-source analytics technologies.

As per some of the studies, project champion (PC) has a positive and significant effect on initiating the adoption of BA (Gu et al., 2012; Puklavec et al., 2018). The project champions are managers who create awareness about the utilities of technology adoption (Gu et al., 2012).

The IT assets are a technology factor and have a significant favorable influence on the BA adoption initiation stage. The IT asset consists of the hardware, software, and data infrastructure for data handling, storage, analysis, and reporting (Verma and Bhattacharyya, 2017). Many studies have found the availability of IT assets in organizations as a critical factor for BA adoption (Alharthi et al., 2017; Lai et al., 2018; Nam et al., 2019; Sun et al., 2018; Verma and Bhattacharyya, 2017).

As per some of the research studies, human assets are a decisive significant factor influencing the BA adoption initiation stage (Ramanathan et al., 2012; Zhu et al., 2006). The technical and business understanding of the employees in the organization has a positive effect on BA adoption evaluation (Ghasemaghaei et al., 2018; Vidgen et al., 2017).

The complexity of BA technologies can also influence the BA adoption evaluation stage. If the managers find it challenging to comprehend the BA technologies, they are less likely to take an affirmative decision on BA adoption. Many studies have found complexity influencing the technology adoption decision (Gangwar and Date, 2016; Hoque et al., 2015; Narwane et al., 2019; Premkumar and Roberts, 1999; Verma and Bhattacharyya, 2017).

As per many studies, the compatibility of technology with organizational business processes, values and policies influence the decision to adopt the technology innovation (Dubey et al., 2017; Sun et al., 2018; Verma and Bhattacharyya, 2017; Wang et al., 2010).

The environmental factors like competition pressure have been found to have a significant favorable influence in the BA adoption initiation stage (Chen et al., 2015; Low et al., 2011; Gangwar, 2018; Wang et al., 2010; Zhu et al., 2006). The high pressure by the competition in terms of revenue, market share, product development can force the organizations to initiate BA projects (Chwelos et al., 2001; Nam et al., 2019; Verma and Bhattacharyya, 2017).

The industry pressure is also found as a significant factor influencing the BA adoption initiation stage (Chwelos et al., 2001; Dutta and Bose, 2015; Levenburg et al., 2006). If a large number of organizations in the industry are using BA, this can influence the organization to start consideration of BA adoption (Verma and Bhattacharyya, 2017).

2.1.2. BA Adoption Stage

The adoption of BA is a distinct stage from the evaluation and initiation of BA (Puklavec, 2018; Zhu et al., 2006). The adoption stage of BA is the decision to use BA for various decision-making in the organization (Zhu et al., 2006). According to the studies on multi-stage adoption of BA suggests, the factors influencing the evaluation stage do not necessarily affect the adoption stage and vice versa (Nam et al., 2019; Puklavec et al., 2018).

The relative advantage as a significant factor influencing technology adoption has received mixed support from the studies. As per some of the studies, the relative advantage is a significant determinant of technology adoption (Alshamaila et al., 2013; Low et al., 2011; Popovič et al., 2012; Wang et al., 2010). According to some of the studies, relative advantage is a non-significant determination of technology adoption (Gangwar and Date, 2016; Puklavec et al., 2018).

The top management support as a factor influences the initiation stages of BA more strongly as that the adoption stage (Chan and Chong, 2013; Puklavec et al., 2018). However, managerial obstacles can negatively influence the adoption of BA in organizations during the adoption stage (Nam et al., 2019; Zhu et al., 2006). The managerial obstacles are the resistance of employees in using BA into their decision-making activities, lack of managerial skills and the lack of top management support (Zhu et al., 2006)

As per Nam et al. (2019), analytics centralization is a significant decisive factor influencing the BA adoption stage. Grossman and Siegel (2014) described analytics centralization as an organizational factor related to the understanding of requirements of various business units and collaborating with the business units for executing analytics projects.

According to Puklavec et al. (2018), the integration of BA with Enterprise Resource Planning (ERP) has a positive and significant influence on BA adoption. The employees are more likely to use comprehensive solutions of BA and ERP than BA technology as an entirely different solution.

Many studies found data quality and data infrastructure as significant factors influencing the adoption stage of BA (Gupta and George, 2016; Nam et al., 2019; Ramamurthy et al., 2008; Verma and Bhattacharyya, 2017). The data quality and data infrastructure are strong predictors of BA in both the evaluation and adoption stages.

As per Nam et al. (2019), the BA adoption stage is less strongly influenced by the competition intensity in the adoption stage as compared to the evaluation and initiation stage (Nam et al., 2019). This finding is similar to the results of the supply chain management adoption stage in a study (Chan and Chong, 2013).

2.1.3. BA Assimilation Stage

The assimilation stage of BA adoption includes the use of BA across various value chain activities for achieving the organizational goals and objectives. The assimilation stage is the final stage of the multi-stage BA adoption model.

As per some of the researchers, organizational factors such as perceived benefits do not influence the routine usage of technology (Chong and Chan, 2012; Puklavec et al., 2018). In contrast, a study on the utilization of software as a service (Saas) found perceived usefulness as a primary factor affecting the continuous usage of the SaaS (Park et al., 2015). Studies have found the top management support as a significant determinant of BA adoption in the BA assimilation stage (Lautenbach et al., 2017; Puklavec et al., 2018). However, the effect of top management support gradually reduces from the evaluation stage to the adoption and assimilation stage (Chan and Chong, 2013).

As per Nam et al. (2019), the analytics centralization has a significant negative influence on the BA assimilation stage (Nam et al., 2019; Zmud, 1982). Nam et al. (2019) reason that the centralization of the analytics function restricts the new usage of BA projects as per the needs of different business units, hence it is not beneficial in the later stages of BA adoption as (Nam et al., 2019).

Most of the studies have uniformity in the findings on data quality and data infrastructure. The data quality and data infrastructure have a significant positive influence on the BA assimilation stage (Nam et al., 2019; Puklavec et al., 2018).

According to Puklavec et al. (2018), the competition intensity is not a significant determinant of BA adoption into the usage and implementation stage. Chan and Chong (2013), in their study on RFID adoption, found that there is no relationship between the successful adoption of technology and the industry trends during the technology implementation stage. Nam et al. (2019) study also provide support to the findings of competition intensity influencing more during the initiation and evaluation stage than the assimilation stage.

2.2. Theoretical Perspectives on Technology Adoption

There are many theoretical frameworks for studying technology adoption. These theoretical frameworks can be suitable for studying technology adoption studied at an individual level or an enterprise level. The major theoretical perspectives for studying technology adoption at an enterprise level are the diffusion of innovations (Rogers, 1995), the resource-based view (RBV), dynamic capabilities, and technology-organizational-environmental (TOE) framework. Next, we review the relevance of each of these theoretical perspectives in the field of BA adoption.

2.2.1. Resource-Based View (RBV)

The resource-based view (Barney, 2001; Wernerfelt, 1984) is a theoretical perspective that explains the role of organizational resources for achieving competitive advantages. Porter (1981) had suggested that organizational resources are the sources of strength that can help in executing organizational strategies. Many studies have used RBV to study the adoption of technology by studying the availability of critical organizational resources such as human assets, technology assets, management capabilities, organizational structure, culture and businesses processes (Caldeira and Ward, 2003; Dubey et al., 2019; Wade and Hulland, 2004; Zhang and Dhaliwal, 2009; Zheng et al., 2013).

2.2.2. Dynamic Capabilities

As per Teece et al. (1997), dynamic capabilities are the firm's capabilities to create, modify, or extend organizational resources in response to environmental changes. The dynamic capabilities of a firm are based on the organizational and managerial processes, the position of the firm, and the firm's path dependencies (Eisenhardt and Martin, 2000; Teece et al., 1997). The dynamic capabilities can help enterprises to identify threats and opportunities, seizing the opportunities and capability to maintain their competitiveness through the reconfiguration of tangible and intangible firm assets (Lin et al., 2016). The Dynamic capabilities of an organization have emerged as a popular theoretical framework towards studying the path of technology adoption in organizations (Akter et al., 2016; Braganza et al., 2017; Dubey et al., 2017; Lim et al., 2011; Nayak et al., 2019).

2.2.3. Technology-Organizational-Environmental (TOE) Framework

TOE framework is an organization level theory and has been used to study IT innovation adoption such as Electronic Data Interchange and e-commerce in organizations (DePietro et al., 1990; Srivastava and Teo, 2007). Many innovation adoptions can be studied from the perspective of organizational context, and the TOE framework is useful in studying these from organizational context (Baker, 2012). The technological, organizational, and environmental factors can be enablers and inhibitors for any technology adoption (Tornatzky and Fleisher, 1990).

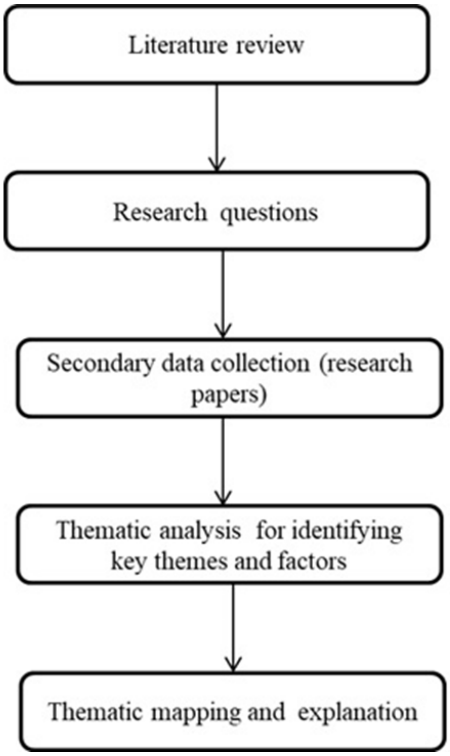
a) Technology context: Technological context describes the characteristics of new technology and also the relevance of the new technology over the existing technology (Oliveira et al., 2014; Zhu and Kraemer, 2005). Technology context explains the influence of internal and external technology factors on innovation adoption (Awa and Ojiabo, 2016; Rui, 2007). According to Rogers (1995), Relative advantage, compatibility, and complexities are the key factor in a technology context.
b) Organizational context: Organizational context refers to the organizational characteristics that are internal to the firm such as firm size, tangible and intangible resources, top management support, perceived benefits and cost of technological adoption (Alshamaila et al., 2013; Kuan and Chau, 2001; Ramamurthy et al., 2008; Tornatzky and Fleischer, 1990).
c) Environmental context: The environmental context consists of the external environment in which the organizations operate their businesses. The external environmental factors significantly influence the adoption of technological innovation in organizations (Low et al., 2011; Zhu et al., 2006). The most popular environmental factors influencing BA adoption are trading partner support, competitive pressure and industry type of the organizations (Chen et al., 2015; Musawa and Wahab, 2012; Picoto et al., 2014; Ramdani et al., 2013).

2.2.4. Diffusion of Innovation

The diffusion of innovations is a widely used theoretical framework to explain the technology adoption process (Kapoor et al., 2014; Rogers, 2003). As per Rogers (1995), there are five elements of innovation diffusion decision making: knowledge, persuasion, decision, implementation, and confirmation. Therefore, the diffusion of BA technologies will happen in multiple stages. The organization will gather information about the BA technologies that will require support from the decision-makers and project champions, followed by the intention to adopt BA and, finally, the implementation and use of BA. As per Rogers (1995), the major determinants influencing the technology adoption process are relative advantage, compatibility, complexity, trialability, and observability.

Ⅲ. Research Methodology

The research on BA adoption is in exploratory stages, and hence qualitative research can be a suitable method for conducting studies on BA adoption (Alshamaila et al., 2013). In the case of the non-availability of sufficient academic papers, the choice of conducting a qualitative method can be used to develop the theoretical framework (Drumwright, 1996; Flint et al., 2002). For example, the researchers in South Korea used the case study method for conducting an exploratory study on cloud computing services (Lee et al., 2014). BA is an exploratory field similar to cloud computing services. The qualitative research method of analyzing text from research papers and trade journals has been used in much technology adoption research (Nasir, 2005; Sun et al., 2018; Verma and Bhattacharyya, 2017). In this study, the thematic content analysis technique has been used to explore the themes from the text of the research papers. Thematic content analysis as a research technique can derive meaningful patterns from large volumes of texts to the context of its use (Patton, 1990). A theme in qualitative research is explained as the attribute, descriptor, element, and concept that describe the data (Vaismoradi et al., 2016). A theme contains codes that have a common point of reference and has a high degree of generality that unifies ideas regarding the subject of inquiry (Bradley et al., 2007; Buetow, 2010). A theme is developed by organizing a group of repeating ideas towards the implicit research topic (Ryan and Bernard, 2003). The research design for this study is described in <Figure 1>.



<Figure 1> Research Design

3.1. Selection of Academic Papers

We initially selected 94 research papers in the field of technology adoption published in high-quality peer-reviewed journals between the years 2000 to 2019. The articles were sourced from online research databases: ProQuest Central, ScienceDirect, and Google Scholar. The above three databases are widely used databases by the researchers, and it also ensures better and adequate coverage of research papers. These papers were selected through an advanced search into these databases with the combination of the following keywords: 'business intelligence adoption,' 'business analytics adoption,' 'big data adoption,' and 'technology adoption' in their title, abstract, or keywords. The selected articles were then manually reviewed to assess their suitability with the research topic. The selected papers were categorized into the studies on the different stages of technology adoption. Additionally, this study identified the most relevant and accessible theoretical perspectives based on their frequencies in these research papers. The four most prominent theoretical perspectives used in technology adoption studies are RBV, dynamic capabilities, TOE framework, and diffusion of innovation. Hence, this study is rigorous to understand the key themes of multi-stage BA adoption using the major theoretical foundations. Finally, a total of 66 academic papers published in 34 high-quality journals were selected as samples. All of the sampled journals are indexed with the Australian Business Deans Council (ABDC) journal quality list as per the publicly available 2019 final list on the ABDC website. Information system research is often interdisciplinary and, therefore, selecting a wide range of journals is more appropriate than choosing articles from a few journals.

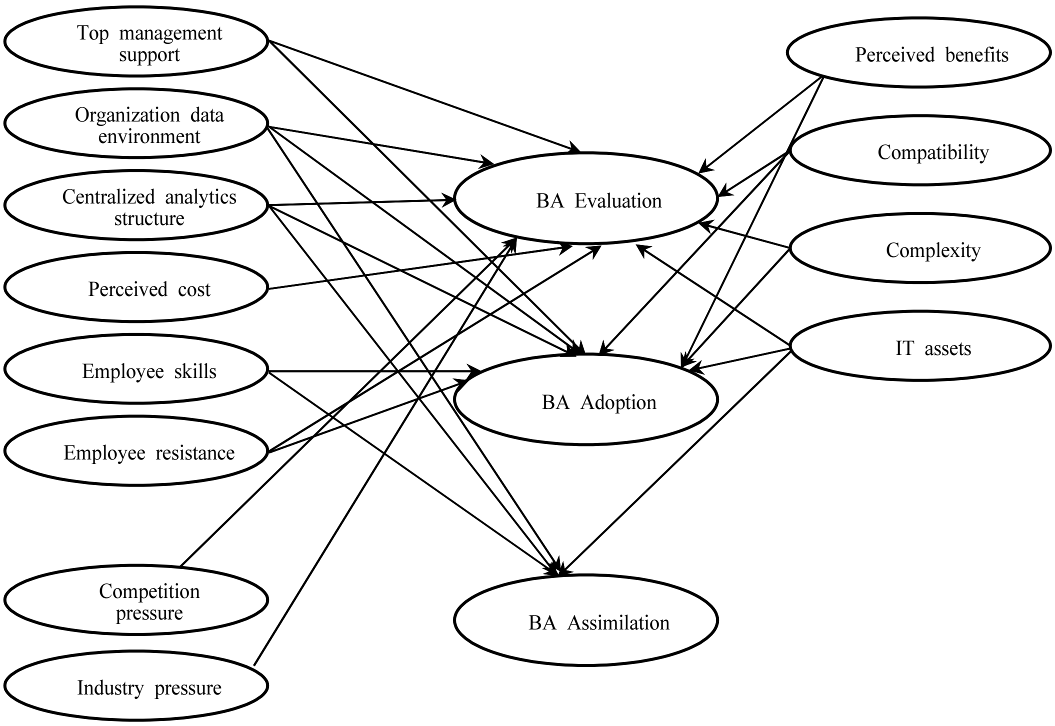
3.2. Data Analysis and Findings

The method suggested by Braun and Clarke (2006) for conducting thematic content analysis was followed. The study was performed in the following steps: thoroughly reading the text and noting down the key ideas, generating codes line by line in the documents, organizing codes into potential themes, reviewing themes, and lastly refining, defining, and naming of the themes. The software program MAXQDA was used for conducting thematic content analysis of the documents. MAXQDA software is helpful for grouping words and phrases which have similar meanings in the context of the research questions into common codes. The papers were grouped according to the different adoption stages of BA adoption in the MAXQDA software. The papers that have studied multiple stages of BA adoption were grouped into various documents groups. The first step of data analysis was to read the selected papers and note down the key ideas emerging from these academic papers. The codes were then generated line by line for each of the documents by two researchers. A total of 17 codes were generated initially. The next round of review of coding was conducted by the two researchers together, and the codes with very low frequency in all the stages of BA adoption were removed from further analysis. For example, trade partner support, customer interaction pressure, and regulatory pressure had very less support from the literature review. Then, the codes were organized into themes based on a common point of reference and similarity in each of the documents. Next, one more round of reviewing the themes was followed. Lastly, the themes were assigned a specific name and definition that was used to identify all the explanations in the documents in context with the themes. The key themes that emerged from the data analysis are organizational characteristics, innovation characteristics, and environmental characteristics. The frequency of the codes under different BA adoption stages and overall was calculated using the MAXQDA software to assess the intensity of each of the codes. The codes are classified as high, medium, and low intensity based on their frequency in the sampled papers. The intensity classification of each of the codes is discussed in <Table 1>.

<Figure 2> represents the conceptual framework for multi-stage BA adoption based on thematic content analysis.

<Table 1> Intensity Classification of Factors Influencing Multi-stage BA Adoption

Key Themes	Codes	BA Adoption Stages		
		Evaluation	Adoption	Assimilation
Organizational characteristics	Top management support	High	High	Low
	Organization data Environment	High	High	High
	Centralized analytics structure	Medium	Low	High (Negative influence)
	Perceived cost	High	Low	Low
	Employee skills	Low	Medium	Medium
	Data based decision making culture	Medium	High	Low
Innovation characteristics	Perceived benefits	High	Medium	Medium
	Complexity	Medium	Medium	Low
	Compatibility	Medium	Medium	Low
	IT assets	High	Medium	Medium
Environmental Characteristics	Competition pressure	High	Low	Low
	Industry pressure	High	Low	Low



<Figure 2> Conceptual Framework for Multi-stage BA Adoption

Ⅳ. Discussions

A total of 12 different factors have emerged from the content analysis of research papers on multi-stage BA adoption. We have discussed the key themes in detail and linked with the theory from the literature review. The 12 factors are categorized into three main themes: organizational characteristics, innovation characteristics and environmental characteristics. This study provides a more holistic representation of the themes influencing BA adoption, as this is the first study to conduct a thematic mapping for multiple stages of BA adoption. This study is one of the few studies that link the factors and themes with multiple theoretical perspectives

4.1. Organizational Characteristics

The organizational characteristics are internal to the firm such as firm size, tangible and intangible resources, top management support, cost of technological adoption, analytics decision-making structure, employee resistance (Alshamaila et al., 2013; Nam et al., 2019; Tornatzky and Fleischer, 1990; Verma and Bhattacharyya, 2017).

4.1.1. Top Management Support

Top management support is the senior management support in providing adequate resources for the adoption of business analytics and creating a supportive climate support (Ramanathan et al., 2017; Wang et al., 2010). Many research papers have found top management as a major construct positively influencing innovation adoption (Dubey et al., 2017; Premkumar and Roberts, 1999; Verma and Bhattacharyya, 2017). As per this study, the top management support is most critical in the evaluation and adoption stage of BA than in the BA assimilation stage (Chan and Chong, 2013; Puklavec et al., 2018). The evaluation and adoption stage of BA require arranging of resources and ensuring the support from many departments of the organization (Ramanathan et al., 2017). This finding is also supported by the theoretical foundation of RBV, which directs at ensuring the availability of adequate resources for initiating an innovation adoption (Caldeira and Ward, 2003; Zhang and Dhaliwal, 2009; Dubey et al., 2019).

4.1.2. Organization Data Environment

Organization data environment is the data management infrastructure for collection, storage, analysis of data, and the data quality in the organization (Kwon et al., 2014; Popovič et al., 2012; Ramamurthy et al., 2008). Many studies support the organization's data environment as a significant determinant of BA adoption (Gandomi and Haider, 2015; Verma and Bhattacharyya, 2017). According to this study, the organization data environment is a critical factor that influences the evaluation, adoption, and assimilation stages of BA adoption significantly. For example, the availability of quality data hindered the process of BA adoption & usage by managers in India (Mathew, 2012; Xavier et al., 2011).

4.1.3. Analytics Decision-Making Structure

The analytics decision-making structure is found to have a mixed influence on BA adoption (Nam et al., 2019). The analytics decision-making structure can be centralized or decentralized in an organization. The centralized structure is the control of decision making by one or only a few teams in the organization (Shepard, 1967; Thompson, 1965). The decentralized analytics decision making structure is the control of analytics projects into individual departments. Only a few studies have studied the influence of analytics decision-making structure in organizations (Grossman and Siegel, 2014; Nam et al., 2019). The centralized analytics structure in an organization is found to have a positive and significant influence in the evaluation and adoption stages but a negative influence in the assimilation stage of BA adoption (Nam et al., 2019).

4.1.4. Perceived Cost

Many Studies on BA adoption support perceived cost as a significant factor influencing BA adoption (Esteves and Curto, 2013; Gangwar, 2018; Verma, 2017; Zheng et al., 2013). Perceived cost acts as an inhibitor of business analytics than an enabler of business analytics (Verma and Bhattacharyya, 2017). As per this study, the perceived cost has a positive and significant influence on the evaluation stage of BA adoption but is not a determinant of the adoption and assimilation stages of BA adoption.

4.1.5. Employee Skills

As per Zhu et al. (2006), the employee's technical capabilities to understand data and analyze data and the understanding of the business domain is critical to innovation adoption. Zhang and Dhaliwal (2009) identified managerial IT knowledge as a key factor influencing the adoption of an IT-enabled supply chain. Xavier et al. (2011), in their study in India, found that inadequate knowledge of analytics among Indian managers partly explains the low adoption of analytics. This study finds that employee skills are less critical during the initiation stage of BA adoption, but the adoption and usage of BA are dependent on the employee's business and technical skills.

4.1.6. Data Based Decision-making Culture

According to Lavalle et al. (2011), the bigger barriers for successful adoption of analytics in large organizations are managerial and cultural factors than data and technology. The analytically advanced companies have a sound data-based decision making culture (Kiron and Shockley, 2011). For example, a big financial services company was highly successful in implementing BA because of the organizational culture of data-based decision making (Cooper et al., 2015). As per this study, the data-based decision making culture is most critical during the adoption stage of BA and least critical during the assimilation stage of BA adoption.

4.2. Innovation Characteristics

Innovation characteristics describe the characteristics of new technology and the relevance of the new technology over the existing technology (Gutierrez et al., 2015; Oliveira et al., 2014). The perceived benefits of innovation is a significant determinant of innovation adoption (Nkhoma and Dang, 2013; Verma and Bhattacharyya, 2017). The complexity of technical innovation is a deterrent for BA adoption and negatively influences technology innovation adoption (Alshamaila et al., 2013; Low et al., 2011).The compatibility of technology with the existing beliefs and business processes in organizations is also a key factor influencing BA adoption (Premkumar et al., 1994; Ramanathan et al., 2017). The findings of innovation characteristics from the content analysis are in alignment with the diffusion of innovation, TOE framework, and RBV that identified relative advantage, compatibility, complexity, and IT assets as major technological factors influencing technology adoption.

4.2.1. Perceived Benefits

Perceived benefits of BA, such as improved sales and profitability, reduced cost of operations; new product development influences the decision to adopt BA (Lai et al., 2018; Verma and Bhattacharyya, 2017). Many research papers support the perceived benefits of technology innovation as a key factor for the adoption of different technology innovations. Premkumar et al. (1994) found perceived benefits as a key factor for EDI adoption. Ramamurthy et al. (2008) found a significant positive influence of perceived benefits on Data Warehouse adoption. Low et al. (2011) validated a significant positive relationship between perceived benefits of cloud computing and its adoption. The perceived benefits have a positive and significant influence in the decision making process towards the evaluation and adoption of analytics. A plausible reason for perceived benefits having less impact in the BA assimilation stage is because the use of BA becomes a natural process in the value chain activities in the BA assimilation stage.

4.2.2. Compatibility

Compatibility by Rogers (2003) is defined as the "degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters." Compatibility as a significant determinant of business analytics has been widely supported in previous studies (Alshamaila et al., 2013; Chen at al., 2015; Verma and Bhattacharyya, 2017; Wang et al., 2010). BA implementation strategy requires effective coordination between the business and technology teams, clearly defined data requirement and sources, identifying variables, developing analytics solutions, and finally measuring the results (Braganza et al., 2017). This study finds that compatibility is a significant determinant in the evaluation and adoption stages of BA adoption.

4.2.3. Complexity

As per Rogers (2003), complexity is the extent to which a technology is easy to understand and use. Complexity acts as an inhibitor of technology adoption (Gangwar, 2018; Narwane et al., 2019; Verma and Bhattacharyya, 2017). The complexity of IT innovation increases the risk of the successful adoption of technology (Premkumar and Roberts, 1999). The effect of complexity on BA adoption stages is mixed (Puklavec et al., 2018). The complexity of BA has a significant impact during the decision-making process for BA adoption, but lesser influence in the BA assimilation stage.

4.2.4. IT Assets

The IT assets are the tools and technologies such as hardware, software, platforms, and databases required for the adoption of technology (Verma and Bhattacharyya, 2017). The compatibility of IT infrastructure is critical for BA adoption (Lai et al., 2018; Ramanathan et al., 2012). IT assets as a critical technology determinant have been widely supported in previous studies (Ramanathan et al., 2012; Verma and Bhattacharyya, 2017). The study finds that IT assets are more critical during the evaluation and adoption stages of BA adoption. The integration of BA technologies with ERP technologies positively influences BA adoption (Puklavec et al., 2018).

4.3. Environmental Characteristics

The environmental context is seen as the external conditions of business operations (Low et al., 2011; Tornatzky and Fleisher, 1990; Zhu et al., 2006). The studies on technology adoption have mainly identified competitive pressure and industry pressure as crucial environmental factors (Musawa and Wahab, 2012; Tornatzky and Fleisher, 1990; Zhu and Kraemer, 2005).

4.3.1. Competition Pressure

Competition pressure is the influence of the competitive environment for the organization to use technology to maintain or increase competitiveness (Chwelos et al., 2001; Hsu et al., 2014). Organizations are likely to adopt technology innovation towards sustainable competitive advantage (Porter and Miller, 1985). The competitive position of a firm is reflected by the specific assets which are specialized in nature and can influence the competitive advantage of the firms (Sambamurthy et al., 2003). Competitive pressure is a significant determinant of BA adoption (Lai et al., 2018; Ramanathan et al., 2017). Organizations experiencing the higher intensity of market share, revenue, market growth, and product development competitiveness are more likely to consider and adopt BA (Chwelos et al., 2001; Verma and Bhattacharyya, 2017). This study finds that the competition pressure is likely to have a stronger influence on the BA evaluation and adoption stages and is less significant in the BA assimilation stage.

4.3.2. Industry Pressure

Industry pressure is the influence of the type of industry to which the organization belongs on technology adoption (Goode and Stevens, 2000). The nature of business requirements in an industry is an important driver for BA adoption (Dutta and Bose, 2015). The firms operating in industries with a large number of customers, transaction volumes have more need for information processing and are likely to adopt BA (Chwelos et al., 2001; Levenburg et al., 2006). The industry pressure acts in the initial adoption stages but does not have much significance during the BA assimilation stage.

V. Conclusions

The success of BA adoption is its role in achieving the strategic and operational goals of the organization. Business analytics adoption is a complex and challenging activity for many organizations as they fail to realize the benefits of BA. There are many research papers that have studied the BA adoption models based on different theoretical perspectives. The research on exploring the dynamics of factors influencing the assimilation stage of BA adoption is scant. The research papers using the theory of RBV, TOE, diffusion of innovation, and Dynamic capabilities have guided the researchers to study technology adoption from the organizational and environmental perspectives along with the technological characteristics. We can securely infer that BA adoption is an organizational activity and is influenced by organizational, technological, and environmental factors in varying intensity.

This study explores explicitly the influence of the technology, organizational and environmental factors influencing the multi-stages of BA adoption. This is a crucial paradigm to explore as the organizations can be in different stages of BA adoption. For example, an organization considering the adoption of BA is going to be dependent on the support from the senior management in the organization. An organization with a higher analytical maturity and regular usage of analytics require fewer advocacies from the senior management. The study finds that the influence of the factors on BA adoption in different stages is different and may not be generalized. The organization data environment and IT assets are a critical factor in all the stages of BA adoption.

The organizations in the evaluation stage of BA adoption require strong top management support, organization data environment, higher perceived benefits of BA adoption, lower perceived costs, ease of technology use, and compatibility with the business needs. A centralized analytics structure is more useful in the evaluation stage of BA adoption. The competition and industry pressure have strong influences in the BA evaluation stage. The organizations moving to the adoption stage also require support from the top management, robust organization data environment, employee skills, perceived benefits, low complexity of BA technologies, and compatibility with the business needs, processes, and values of the organizations. There are a less number of factors influencing in the assimilation stage of BA adoption. The assimilation stage of BA adoption is controlled by the organization's data environment, decentralized analytics structure, employee skills, perceived benefits, and IT assets. In the context of BA, this study proposes a conceptual framework to study the multi-stage adoption using multiple theoretical perspectives.

Ⅵ. Implications and Limitations

This study contributes to the existing knowledge in the field of BA adoption, especially from the perspective of multi-stage BA adoption. This research can be useful for practicing managers in developing an operational framework for business analytics adoption. Future research can validate the themes and factors discussed in this research paper in different countries and across industries. Also, future research can confirm the factors influencing BA adoption in multiple stages. The next research can also elaborate on the path from the initiation stage to the adoption and assimilation stages.

A limitation of this study is that it does not analyze the factors influencing BA adoption as per different industries and geographies. The other limitation of this study is the dependence of findings based only on the secondary data. A combination of primary and secondary data can make the conclusions more reliable than using one data source. Finally, the findings of this study explain the factors influencing the initiation, adoption, and assimilation stages of BA. Still, this study does not probe the sequential path from initiation to adoption and assimilation.

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◆ About the Authors ◆

Amit Kumar

Amit Kumar is a Doctoral candidate at NMIMS, School of Business Management, Mumbai, India. He has an MBA in international business from Indian Institute of Foreign Trade, New Delhi, India. He currently teaches at NMIMS, ASM School of Commerce, Mumbai, India. His interest areas are technology management, marketing analytics and business strategy.

Bala Krishnamoorthy

Bala Krishnamoorthy is Associate Dean and Professor in Strategy at NMIMS, School of Business Management, Mumbai, India. She has published many papers and case studies in international journals and is a guide for the doctoral programme in management. She is a rank holder at post graduate degree, University of Madras and a Ph.D. from JBIMS, University of Mumbai.

Divakar B Kamath

Divakar B Kamath is a Director, Google Cloud, India and is based in Mumbai. He completed his MBA from JBIMS, Mumbai, India and his Ph.D. from Mumbai University. He has worked extensively across telecommunication, media and entertainment verticals in Information Technology industry.

Submitted: November 18, 2019; 1st Revision: March 19, 2020; Accepted: March 24, 2020