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# An extension of the technology acceptance model in the big data analytics system implementation environment

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ABSTRACT

Research on the adoption of systems for big data analytics has drawn enormous attention in Information Systems research. This study extends big data analytics adoption research by examining the effects of system characteristics on the attitude of managers towards the usage of big data analytics systems. A research model has been proposed in this study based on an extensive review of literature pertaining to the Technology Acceptance Model, with further validation by a survey of 150 big data analytics users. Results of this survey confirm that characteristics of the big data analytics system have significant direct and indirect effects on belief in the benefits of big data analytics systems and perceived usefulness, attitude and adoption. Moreover, there are mediation effects that exist among the system characteristics, benefits of big data analytics systems, perceived usefulness and the attitude towards using big data analytics system. This study expands the existing body of knowledge on the adoption of big data analytics systems, and benefits big data analytics providers and vendors while helping in the formulation of their business models.

## 1. Introduction

Given the popularity of digital devices such as personal digital assistants, mobile phones and laptops, and increasing usage of the Internet and social media, the volume of user-generated data has been increasing rapidly in emerging economies like India (Verma & Bhattacharyya, 2016). In India, 66% of the 180 million Internet users regularly access social media platforms, and their numbers are estimated to reach 283 million by 2018 (IAMAI, 2015). Analysing such user-generated data can help in identifying business opportunities for firms in emerging economies (Dubey, Gunasekaran, Childe, Wamba, & Papadopoulos, 2016). Big Data Analytics (BDA) comprises of techniques and technologies to capture, store, transfer, analyse and visualise enormous amount of structured and unstructured data (Erevelles, Fukawa, & Swayne, 2016). Due to fierce competition in the turbulent market environment of emerging economies, firms are adopting state-of-the-art information technologies for competitive advantage (Verma & Bhattacharyya, 2017), BDA being one of them. BDA enables firms to conduct their businesses in more efficient and effective ways by improving customer services, and empowering marketing and sales force (Chen & Zhang, 2014). One can, however, argue that not every firm in emerging economies intends to adopt the BDA technology despite possessing traditional business intelligence and analytics systems (Dubey et al., 2016). In a survey conducted by Qlik in 2015, out of 350 Indian firms surveyed, only 21% of the participating firms had implemented BDA systems, while 42% of the participating firms were potential adopters (Rigby & Bilodeau, 2015). Therefore, in this

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study, the authors attempt to understand the motivating factors among firms that prompt the business decision to adopt BDA systems.

The rapid growth in the usage of digital devices like smartphones, tablets, and Internet of things by consumers and suppliers has added to data complexity and led to the beginning of the BDA era (Bhimani & Willcocks, 2014). BDA can be conceptualised as a suite of data management and analytical techniques for handling very large (from terabytes and exabytes) and complex (from sensor to social media) data. Further, the BDA infrastructure requires advanced data storage, management, analysis and visualised technologies (Chen, Chiang, & Storey, 2012). Gandomi and Haider (2015) referred to BDA as a computation technique with five characteristics, namely, volume, velocity, variety, veracity and value. Because of these five BDA characteristics are posing challenges in delivering business-critical information to both big and small firms alike (White, 2012). Therefore, firms now need data analysts with skills to validate and interpret big data and manage a firm's search applications. Demirkan and Delen (2013) proposed three service models for BDA, namely, Data-as-a-Service, Information-as-a-Service and Analytics-as-a-Service. BDA has led to a paradigm shift towards data-intensive scientific discovery. However, this also comes with several challenges like difficulties in data capturing, data storage, data analysis and data visualisation (Nudurupati, Tebboune, & Hardman, 2016).

BDA is becoming an important asset for business managers due to its ability of creating information and knowledge value. The ability of BDA to identify problems and opportunities from internal and external unstructured data of customers and market could provide cumulative value and knowledge to managers (Chen & Zhang, 2014). As the amount of data continues to grow exponentially, firms from different sectors are becoming more interested in managing and analysing big data. Thus, firms are rushing to seize opportunities offered by BDA and gain benefits from these insights (Erevelles et al., 2016). Consequently, adopting BDA for better and real-time decision-making has the potency to unlock economic value. BDA could create value for a firm by revealing previously unseen patterns, sentiments, and customer intelligence, among other factors (Elgendy & Elragal, 2014). BDA could create value for a firm such as improved performance, customer intelligence, fraud detection, quality and risk management, and supply chain intelligence (Ji-fan Ren, Fosso Wamba, Akter, Dubey, & Childe, 2016). BDA enables firms to enhance existing products, create new services and products and invent entirely new business models. Industries where BDA can unlock new increased economic value include retail, healthcare, manufacturing, banking, telecom and government administration (Elgendy & Elragal, 2014). Using BDA firms can monitor customer sentiments towards brands, comprehend trends, perform direct marketing functions and identify influential individuals (Shen, Wei, Sundaresan, & Ma, 2012). BDA can enable firms to construct predictive models for customer behaviour and purchase patterns, enabling micro-segmentation of customers for targeted promotions and focused advertising. These will finally lead to enhanced profitability for firms (Gandomi & Haider, 2015).

Application of BDA helps analyse geospatial data and stock utilisation on deliveries, which provides insights to manufacturing and retail firms (Erevelles et al., 2016). These insights could enable firm managers to get demand forecast in real-time, automate replacement decisions and identify root causes of cost inefficiency (Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). These measures could reduce lead times, costs, delays and process interruptions, thereby ultimately creating value. Furthermore, from the supplier side, the quality or price competitiveness can be improved by analysing the supplier's data to monitor performance (Ji-fan Ren et al., 2016). BDA can also minimise performance variability and prevent quality issues by reducing scrap rates and decreasing the time to market (Elgendy & Elragal, 2014). In healthcare, BDA can create value by improving quality and efficiency of services, and by integrating patient data across different departments and institutions (Gandomi & Haider, 2015). BDA can also provide diverse real-time information on aspects such as traffic and weather. BDA can create value for the banking sector by enabling quantification of various operational risks. BDA can even be used to identify networks of collaborating fraudsters, or discover evidence of fraudulent insurance or benefits claims. This may ultimately lead to the disclosures of hitherto unnoticed fraudulent activities (Elgendy & Elragal, 2014).

Given the benefits of BDA systems, it is important to look into the facts that drive BDA adoption in firms. Factors that have been identified for achieving implementation success of BDA systems include top management support (Gunasekaran et al., 2017), big data quality (Kwon, Lee, & Shin, 2014), and well-defined employee roles, including chief technology officers and functional managers (Constantiou & Kallinikos, 2015). BDA implementations require modifications in the existing business process because of the need to adapt organisational processes to match the capabilities of the system (Wang, Gunasekaran, Ngai, & Papadopoulos, 2016). BDA systems are inter-organisational systems and their implementation involves multiple stakeholders from different geographically dispersed locations. BDA systems require standardisation of big data and integration of the system with other information systems. Thus, there is a need to manage several vendors and service providers (Chen & Zhang, 2014). Traditional information systems project management challenges increase manifold in such environments, making BDA implementation more expensive, difficult and failure-prone (Nudurupati et al., 2016). Thus, the results obtained in other traditional technologies like data warehousing and business intelligence implementation environments have not been readily applied to complex BDA systems.

Several research studies have attempted to explain the use and adoption of new information system. However, none of the existing models, frameworks and theories fully explain the reasons for acceptance or rejection of a particular information system (Gangwar, Date, & Ramaswamy, 2015). In order to decrease the attrition of implementation of new information system, it is important to understand the benefits of BDA systems and factors that lead to either negative or positive attitudes towards information systems (Liao & Tsou, 2009). Resistance towards new information system tools like BDA might be attributed to discontented users of a firm that, in turn, might reduce overall organisational performance in the short run (Waller & Fawcett, 2013).

Presently, a vast amount of data related to business processes and customers is being exchanged between buyers, sellers, and competitors. Adoption of BDA systems could lead to changes in business procedures, managerial power and organisational structures (Chen, Preston, & Swink, 2015). Implementation of BDA systems might lead to a higher level of transparency, as BDA supports sharing of information and data across business processes and firm value chain (Gunasekaran et al., 2017). BDA could enable firms to gather, compile and distribute information and establish links amongst trading partners (Kwon et al., 2014). This makes system characteristics (i.e., information and system quality) of BDA systems a critical factor for its adoption (Shin, 2015a, 2015b). However, these variables were not addressed in previous research studies as determining factors for BDA adoption. This literature gap provides the motivation for this research study. Hence, the objective of this research study is to extend previous studies, particularly Technology Acceptance Model (TAM), and construct a research model that includes system characteristics (i.e., information and system quality) as a salient factor affecting the attitude towards BDA adoption and usage in organisations. Thus, the research questions are: (1) Do system characteristics impact managerial perception in the benefits, perceived ease of use, usefulness, and attitudes toward using BDA systems; (2) Do BDA users form a favourable attitude toward using BDA system, and eventually adopt the system.

This study theoretically enlarges the scope of the adoption decision to explicitly include both the characteristics and perceived benefits of BDA systems. The research study may benefit practitioners by offering an increased understanding of business managers' perception of the benefits, usefulness and ease of BDA systems that can be used, in turn, to encourage the adoption of BDA systems. Therefore, the objectives of this study are as follows:

1. To investigate whether the characteristics of BDA system, managerial beliefs in its benefits, perceived ease of use and perceived usefulness significantly impact managers' behavioural intention to adopt BDA systems.
2. To understand the mediation effect of the identified factors impacting the adoption of BDA systems.
3. To evaluate whether the technology acceptance model provides a solid theoretical basis for examining the adoption of BDA systems in Indian firms.

The remainder of this research paper is organised as follows: results of a detailed literature review have been provided in Section 2, whereas the research model and hypotheses have been developed in Section 3. Research design has been outlined in Section 4 while data analysis and results have been discussed in Section 5. Finally, based on the findings of this research study, conclusions and implications have been presented.

## 2. Literature review

### 2.1. BDA implementation research

TAM has been widely used to examine user acceptance of various technologies in organisations, such as enterprise resource planning (Amoako-Gyampah & Salam, 2004), customer relationship management (Wu and Wu, 2005), cloud computing (Gangwar et al., 2015), Software as a Service (Wu, 2011), and data warehousing (Wixom & Todd, 2005). In the case of BDA systems, however, their characteristics and unique usage-context factors must also be taken into account (Ji-fan Ren et al., 2016). With the rapid spread of BDA techniques and technologies, TAM has been used to investigate acceptance of that technology. Soon, Lee, and Boursier (2016) employed integrated TAM to examine the extent of adoption of big data by adding variables like perceived benefits, perceived risk and predictive analytics accuracy. According to their results, predictive analytics accuracy and perceived risk were strong predictors of big data adoption.

Kim, Lee, and Seo (2013) proposed a conceptual extended form of TAM to investigate acceptance of big data by adding organisation innovativeness, organisation slack, information system infrastructure maturity and perceived benefits as external variables. Rahman (2016) proposed a big data adoption model that incorporated system characteristics like flexibility, scalability, data storage and processing into TAM to understand the influence of system characteristics on big data adoption. However, despite the BDA systems receiving fairly extensive attention, the review of literature failed to reveal a rigorous effort to explore the factors that affect adoption of BDA systems among business managers of firms in emerging economies like India. Existing research focuses mainly on the impact of firms' business environment on BDA system adoption and benefits and risks associated with the same. Since the decision to use BDA systems in firms is also determined by the intentions of the employees and not only by the cost benefit analysis and business environment, the factors that affect adoption of technology at the individual level also need to be assessed.

### 2.2. Technology acceptance model (TAM)

The key measures of IS implementation success include the intended level of usage of the IT. System usage includes the acceptance of the technology by users (Aggelidis & Chatzoglou, 2009). TAM has been used by several previous IT research studies dealing with behavioural intentions and usage of IT (Cheung & Vogel, 2013; Lee, Hsieh, & Hsu, 2011). TAM is an adaptation of the theory of reasoned action model developed by Fishbein and Ajzen (1997). This model was specifically developed for modelling user acceptance of information systems with the aim of explaining the behavioural intention to use the system (Hsu & Lin, 2008). As per TAM, perceived ease of use and perceived usefulness are of prime relevance in explaining the behavioural intention to use IT systems (Fig. 1). Perceived ease of use refers to the degree to which an individual believes that using a particular system would be free of effort (Verkasalo, López-Nicolás, Molina-Castillo, & Bouwman, 2010). On the other hand, perceived usefulness refers to the degree to which an individual believes that using a particular system would enhance job performance (Huang, Quaddus, Rowe, & Lai, 2011). TAM posits that information system usage is determined by a behavioural intention to use the system, where the intention to use information system is determined by an individual's attitude toward using the system and its perceived usefulness. Several research studies have extended this theory to examine the antecedents of the two belief constructs of TAM. Amoako-Gyampah and Salam (2004) argued that a better understanding of these belief constructs could help in designing effective organisational interventions, which finally lead to increased user acceptance and use of new information system. This attitude, in turn, leads to the behavioural intention to adopt information

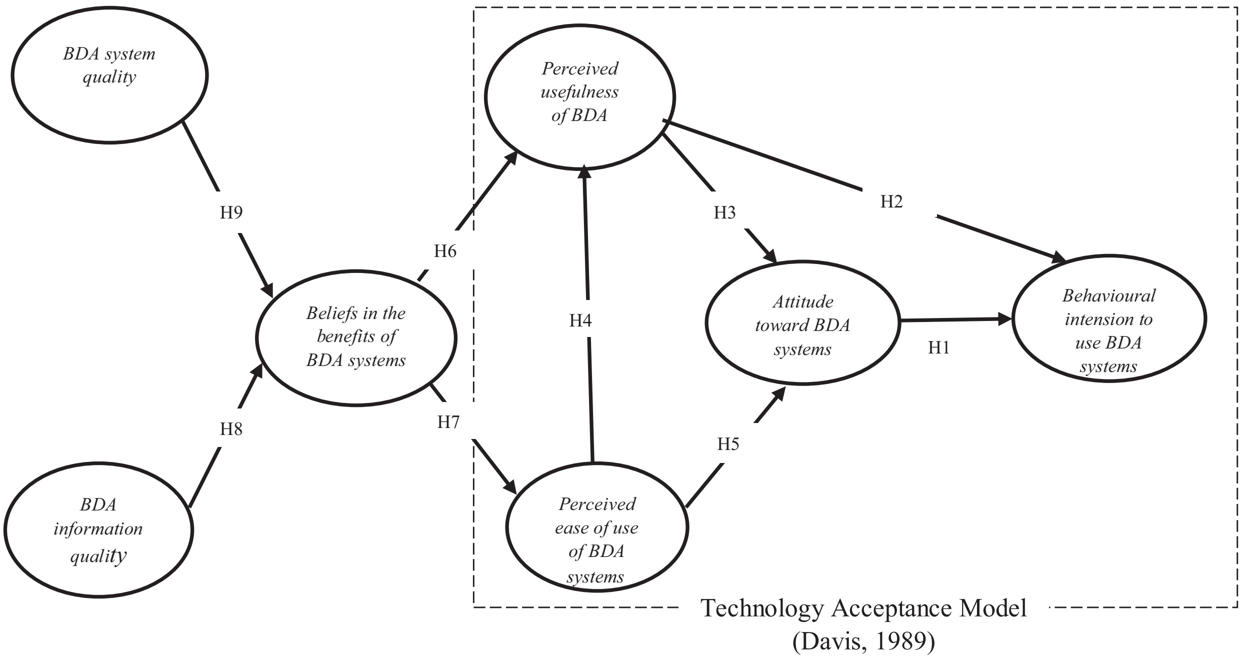


**Fig. 1.** The proposed research model.

system, and thus, translates into actual usage behaviour (Liao & Tsou, 2009). Also, users' beliefs of usefulness have an indirect influence on intention *via* attitude. Finally, users' perceived usefulness is influenced by perceived ease of use.

Like theory of reasoned action, in TAM, attitude is an important mediator between perception and behavioural intention. However, few studies have also indicated that the link between attitude and behavioural intention has a non-significant effect (Padilla-MeléNdez, Del Aguila-Obra, & Garrido-Moreno, 2013). They explained this result by addressing the fact that an individual may use information systems even if they do not have a positive attitude towards it because it might enhance their productivity. However, Venkatesh, Morris, Davis, and Davis (2003) argue that attitude has a significant influence on intention only when constructs related to performance and effort expectancies are not included in the model. Several previous researchers have incorporated some constructs other than that originally suggested in TAM, such as perceived enjoyment (Davis, Bagozzi, & Warshaw, 1989), output quality, social influence (subjective norm, voluntariness and image) and cognitive instruments (job relevance, output quality, and result demonstrability) (Venkatesh & Davis, 2000). The inconsistency in the mediating role of attitude in TAM may be due to consideration of too many constructs in different extended TAM, which might dilute the attitudinal influence on intention (Wu, Cheng, Yen, & Huang, 2011). Thus, in this study, the constructs of the original TAM were included in the proposed research model to understand the causal order of the related mediators.

## 3. Research model and hypotheses development

The goal of this study is to examine the influence of antecedent variables on the two belief constructs of TAM, i.e., perceived ease of use and perceived usefulness. Studying the impact of external factors on the TAM core constructs not only contributes to theory development but also helps in designing appropriate system characteristics, such as system quality and information quality. Thus, it might lead to improved technology acceptance. This is particularly important in the case of BDA systems. The proposed model is depicted in Fig. 1. The research model has the core TAM constructs and postulated relationships. This study hypothesised that user beliefs in the benefits of BDA system, BDA system quality and BDA information quality would influence perceived ease of use and perceived usefulness and subsequently, behavioural intention to use a BDA system.

### *3.1. Attitude towards BDA systems*

According to Park (2000), an individual's intention to exhibit a specific behaviour is determined by assessing subjective norms and attitudes. In the TRA model, attitude is referred to as the feeling of affection or contradiction for some objects (Park, 2000). The main dependent variable in this study is the intention to use. Behavioural intention to use a technology is the degree to which an individual is interested in using a technology. According to Lin, Fofanah, and Liang (2011), an individual's attitude towards using a technology is a key mediator of influence with other external variables on the intention to use that technology in TAM. A positive relationship between attitude towards a new technology and intention to use has been reported in several previous studies (Amoako-Gyampah & Salam, 2004). BDA systems are complex real-time decision-making systems and implemented to replace traditional database and business analytics systems (Chen et al., 2012). The usage of BDA system incorporates both mandatory as well as discretionary usage. The mandatory usage of BDA systems includes a basal level needed to perform minimal job functions; on the other hand, usage beyond this level may become voluntary for larger, more broad-based IT functions (Demirkan & Delen, 2013). Previous research studies proposed that perceived voluntariness is important in the acceptance and usage of information system (Sharif Abbasi, Hussain Chandio, Fatah Soomro, & Shah, 2011). Also, mandatory usage of information system is likely to lead to firm-level benefits, ensuring enhanced efficiency. The value of a BDA system may lie in its efficient and effective usage (Mortenson, Doherty, & Robinson, 2015). The participation of the business managers can be effective if they believe that they have control over the outcome of their efforts (Nudurupati et al., 2016). If the usage of BDA systems is mandated, there would be variations in the intentions of the users (Chen et al., 2015). It is important to examine behavioural intention to use the BDA systems even when usage might be mandatory. Therefore, this study proposed a hypothesis that applies and extends the theory of reasoned action-based relationship between attitude and intention to the context of BDA systems.

**H1.** *Attitude toward BDA systems will have positive effects on behavioural intention to use the BDA systems.*

### 3.2. Perceived usefulness

TAM posits that perceived usefulness and perceived ease of use are strong predictors of attitude toward and intention to use specific information systems and services (Davis, 1992). Perceived usefulness examines the extrinsic characteristics of an information system, including task-oriented outcomes and objectives such as task efficiency and effectiveness (Wixom & Todd, 2005). Perceived ease of use examines the intrinsic characteristics of information system, including ease of use, flexibility and clarity (Gangwar et al., 2015). Several studies (e.g., Park, Roman, Lee, & Chung, 2009; Shaikh & Karjaluoto, 2015) have used the TAM model to study the impact of perceived usefulness on user attitude and behavioural intention. Moreover, TAM incorporates that perceived ease of use has a direct influence on perceived usefulness because an easier system requires less effort for task accomplishment (Kuo & Lee, 2009). User individuals who perceive a higher usefulness of BDA system would be more willing to adopt it (Amoako-Gyampah & Salam, 2004). Ease of use would be a primary factor to strengthen the acceptance of BDA system and encourage an increased sense of usefulness (Gangwar, Date, & Raoot, 2014).

Perceived usefulness is defined as the degree to which an individual believes that the use of an innovation helps in enhancing her/his work. Several research studies have demonstrated that perceived usefulness is a strong determinant of an individual's intention to adopt technology (Kulviwat et al., 2007; Wu & Wang, 2005; Yen, Wu, Cheng, & Huang, 2010). Perceived usefulness has been identified as the most significant factor in the acceptance of a new technology (Wu & Wang, 2005; Yen et al., 2010). In firm-level studies, perceived usefulness of a technology has been found to be even more important than perceived ease of use (Wu & Wang, 2005). If business managers perceive that the use of a new technology is likely to enhance job performance and productivity, it would have a favourable influence on the attitude and intention to adopt technology. Therefore, following two hypotheses are proposed:

**H2.** *Perceived usefulness will have positive effects on behavioural intention to use the BDA systems.*

**H3.** *Perceived usefulness will have positive effects on attitude toward BDA systems.*

### 3.3. Perceived ease of use (PEU)

Ease of use is the degree to which an individual believes that using an innovation will be free of effort. Before making a decision to adopt a new technology, it is important to understand the complexity associated with the new technology. Behavioural intention of an individual to adopt an innovation will increase, if the individual believes that the technology adoption will be free of effort (Lee, Ramayah, & Zakaria, 2012). In the era of complex working environments and rapidly changing technologies, the intent of business managers to adopt an innovation increases if they perceive that the new technology is flexible, easy to understand, controllable and convenient to operate (Kuo & Lee, 2009).

The effect of perceived ease of use on the adoption intention of a technology has been empirically tested in numerous studies (Ayeh, Au, & Law, 2013; Kim et al., 2013; Zailani, Iranmanesh, Nikbin, & Beng, 2015). In several cases, perceived ease of use has been shown to have both direct as well as indirect effects on adoption intention (Ayeh et al., 2013), whereas in some cases it had an indirect effect through perceived usefulness (Gangwar et al., 2015). The direct effects depict that perceived ease of use could improve an individual's attitude toward adopting a new technology regardless of the technology's usefulness. However, the indirect effect of perceived ease of use suggested that if a new technology is easier to use, individuals would perceive it as more useful. This will finally shape a more positive attitude and intention toward using the innovation (Davis et al., 1989). Therefore, the following two hypotheses have been developed:

**H4.** *Perceived ease of use will have positive effects on perceived usefulness of BDA systems.*

**H5.** *Perceived ease of use will have positive effects on attitude toward BDA systems.*

### 3.4. Beliefs in the benefits of BDA systems (BNEB)

Beliefs about a technology provide the basis for attitude formation toward the technology (Muk & Chung, 2015). The understanding of beliefs and belief formation processes about an information system increases the understanding of how IT system characteristics, such as system quality and information quality, can be used to shape beliefs. This, therefore, impacts behavioural intention to use a given information system (Zheng, Zhao, & Stylianou, 2013). BDA systems span across functional boundaries. BNEB is an inter-organisational IT application designed to provide a unified view of organisational processes (Dubey et al., 2016). This system involves several users at different organisational levels for implementation. Successful implementation of BDA systems involves mutual trust and commitment between various stakeholders to ensure a free exchange of beliefs and opinions (Shin, 2015a, 2015b). Shared belief about the benefits of an information system project allows organisational participants to find common grounds and a shared sense of purpose (Ramayah & Lo, 2007). Since information system benefits at multiple levels are complex and subtle (Kamhawi, 2008), users of the application form beliefs about the benefits at the individual level. The users of complex information system also share beliefs with peers and managers about these benefits. This implies that business managers may be able to impact belief about the BDA system through system characteristics and information gathering processes for decision-making. The BNEB plays an important role in shaping the usage intentions of BDA systems (Shin & Choi, 2015). This affirmation differs from the PU belief of TAM. Perceived usefulness explains the belief related to the performance of the users and how a particular system would enhance job performance (Palacios-Marqués, Cortés-Grao, & Carral, 2013). However, BNEB details should be shared with peers and business managers for realisation of the value of the BDA system. Since users of BDA systems form a shared belief, it is theorised that it will have a positive effect on the perceived usefulness of the BDA system.

BNEB could also influence the perceived ease of use of BDA systems due to its associated complexity (Chen et al., 2015). Compared to traditional business analytics technologies, BDA systems not only require that business managers understand them but they should also find the system's interface easy to use (Dutta & Bose, 2015). Business managers should also understand the business implications and the changes made through the BDA system (Constantiou & Kallinikos, 2015). Several previous researchers have argued that perceived ease of use of a new technology might be influenced by actions and statements of significant peers and supervisors (Gangwar et al., 2015; Wu et al., 2011). This study proposes that the perceived ease of use of BDA systems might be influenced by the extent to which a user believes that the BDA systems will be beneficial. Therefore, the following hypotheses are proposed:

**H6.** *Beliefs in the benefits of BDA systems will have positive effects on perceived usefulness of BDA systems.*

**H7.** *Beliefs in the benefits of BDA systems will have positive effects on perceived ease of use of BDA systems.*

### 3.5. Information quality

In the era of BDA, data originates from various sources; this leads to the need of an integrated platform or system for aligning heterogeneous data and creating holistic organisation-wide information (Dubey et al., 2016). Therefore, the system characteristics, which include system quality and information quality, become a critical concern for decision-makers (Hashem et al., 2015). Information might be incorrect or inappropriately interpreted by users who do not understand the complexities and implications of BDA systems (Russell Neuman, Guggenheim, Mo Jang, & Bae, 2014). Wang and Liao (2008) referred system quality as the perceived level of general performance of a particular system and information quality as the user's perception of the output quality generated by an IT system. It involves factors like accuracy, reliability, completeness and timeliness. Several researchers have found the positive relationship between system characteristics (i.e., system quality and information quality) and user's perception regarding the system (Pai & Huang, 2011; Zheng et al., 2013). Zheng et al. (2013) found that both information quality and system quality are significant determinants of intention to use ERP. Users are unlikely to commit to sharing and updating of system and information unless they find the system valuable (Lin, 2010).

Information quality is the user's perception of the output quality generated by an information system and it encompasses factors like accuracy, reliability, completeness and timeliness (DeLone and McLean, 1992). If the information provided by an information system application does not conform to the needs of its users, the users will not realise the benefits associated with the technology and the firm will lose business because of non-adoption of the technology (Clikeman, 1999). Big data quality is the heart of information quality of BDA. A poor/irrelevant big data quality would lead to poor information quality that, in turn, could have adverse effects on operational, tactical and strategic decision-making (Ji-fan Ren et al., 2016). High BDA information quality (i.e., accuracy, completeness and reliability) can lead to high benefits to firms like internal organisational efficiency (high quality decision-making) (Ochieng, 2015). On the other hand, inaccurate or delayed information from big data would make the selection and execution of a sound business strategy difficult (Ji-fan Ren et al., 2016).Thus, high information content (i.e. reliability, accuracy, timeliness and completeness of information) would lead to better perception in the benefits associated with the new information system application. Thus, the following hypothesis is proposed:

**H8.** *Information quality will have positive effects on beliefs in the benefits of BDA systems.*

### 3.6. System quality

System quality denotes the quality of the information processed by the system (Lin et al., 2011). System quality also measures the degree to which the system is technically sound (Aggelidis & Chatzoglou, 2009). It is measured by attributes like functionality, flexibility, sophistication, system features, system accuracy and integration (Delone & McLean, 2003; Sedera & Gable, 2004). A well-designed, developed and implemented system is an important requirement to derive organisational benefits like increased revenue, cost reduction and improved process efficiency (Bakos, 1991). On the other hand, a system which is not well design would be detrimental to business operations and result in increased product cost for the organisation (Lin et al., 2011). For instance, the system quality of data warehousing has been positively associated with perceived net benefits of individual productivity and ease of decision-making, thus, finally leading to increased organisational efficiency (Wixom and Watson, 2001). To create business value for an organisation, it is important to ensure efficient delivery of system with accessibility and availability (Ji-fan Ren et al., 2016). Furthermore, information system should be of high quality to increase the user's perception in the benefits associated with the new information system.

The decision to adopt a BDA system is very likely to depend upon the characteristics of the system. Good system characteristics propagate the perception of benefits of technology from one user to the other, which in turn, increases the shared belief about the benefits of the BDA systems (Nudurupati et al., 2016). The ability to influence behavioural intention of BDA system usage is dependent on factors like the accuracy and frequency of information (Waller & Fawcett, 2013). Therefore, it is expected that perceptions about the usefulness of the BDA systems will also be dependent on the amount and quality of information provided by the BDA systems. Effective systems and information quality would lead to the development of trust in information needed for process changes and ultimately, to the acceptance of BDA systems (Wamba et al., 2015). One of the goals of system characteristics is to influence attitude and behaviour (Sánchez & Hueros, 2010). System characteristics impact behavioural change through a change in attitude (Zheng et al., 2013). Therefore, it could be assumed that user's behaviour cannot be determined in advance, and hence, system characteristics would influence the behavioural intention to use BDA systems. The proposed research model suggests that BDA system characteristics (like system quality and information quality) will impact shared belief about the benefits of the BDA systems. This impact on shared belief would further have an influence on perceived usefulness and perceived ease of use of BDA systems, which would subsequently influence attitude and behavioural intention of BDA implementation and usage. Thus, the following hypothesis is proposed:

**H9.** *System quality will have positive effects on beliefs in the benefits of BDA systems.*

## 4. Study design

### *4.1. Measurement development*

In the initial version of the survey questionnaire designed for this study, items were extracted from various previous research studies and adapted for this research (Al-Jabri & Roztocki, 2015; Terzis, Moridis, & Economides, 2013). The final survey questionnaire was divided into two parts. The first part consisted of questions for collecting demographic and organisational information of the respondents, such as their role in the organisation, number of employees and turnover. The second part included the measures of the theoretical constructs of the proposed research model, namely, information quality, system quality, beliefs in the benefits of BDA systems, perceived usefulness, perceived ease of use, attitude and behavioural intention. In this study, the measures of perceived usefulness and perceived ease of use were adapted from previous studies relating to the TAM model of Al-Jabri and Roztocki (2015) and Terzis et al. (2013). Behavioural intention and attitude measures were derived from Jabra and Roztocki (2015) and Toft, Schuitema, and Thøgersen (2014). Measures of information quality and system quality were adapted from Shin (2015a, 2015b) and Zheng et al. (2013). To address the indicators of BNEB, the measures of Amoako-Gyampah and Salam (2004) were used. Constructs in this study were measured using a five-point Likert scale, ranging from “strongly disagree” (1) to “strongly agree” (5) (Zheng et al., 2013). The adaptation process involved rewording the measurement items to fit the context of BDA system adoption. The draft questionnaire was reviewed by academics and industry experts to identify possible problems in terms of clarity and accuracy. The wordings of few items were modified according to the experts’ feedback. The final questionnaire items are included in Table 1.

### *4.2. Sample and data collection*

The target population comprised of individuals experienced in data management and advanced analytics systems like Hadoop, MapReduce, Netezza, SAP Hana, SQL stream s-Server, Tableau, Apache mahout or any other BDA system. These individuals were business managers, users, developers, consultants or others. Data was collected in India through online survey. The convenience sampling procedure, using the respondent-driven sampling method (Al-Jabri and Roztocki, 2015), was conducted by sending e-mails to potential respondents who were also asked to forward it to their co-workers. The e-mail consisted of a brief description of the objectives of the study and a link to the survey. The online survey was also posted on social media platforms like LinkedIn and Facebook. The participants were located in different regions of India and worked in different units of the organisations. A total of 156 responses were obtained, representing a response rate of 23%. Of the 156 responses, six were incomplete and were, therefore, dropped from subsequent analysis, yielding 150 usable responses. T-test was used to assess the non-response bias. A comparison between early ($N$ = 87) and late respondents ($N$ = 63) showed no significant differences at the 0.05 significant level. Table 2 tabulates the characteristics of the respondents and of the organisations in which they work. The respondents’ positions in the firms varied from senior managers (31.8%) to CXO level (15.9%). The firms varied in size from large to small, as the number of employees working in these firms ranged from more than 800 (49.1%) to less than 250 (24.1%). Companies with a turn over greater than INR 3000 million were the largest fraction of the respondents of this study.

**Table 1**
Construct with items of the survey instrument.

| Constructs | Item | Measure | Source |
|---|---|---|---|
| *Behavioral intension to use BDA systems (BI)* | BI1 | I am excited about using the BDA systems in my workplace | Jabra and Roztocki (2015) |
| | BI2 | It is my desire to see the full utilisation and deployment of the BDA systems | Jabra and Roztocki (2015) |
| *Attitude toward BDA systems (ATT)* | ATT1 | The BDA systems will make real-time decision making easier | Toft et al. (2014) |
| | ATT2 | The BDA systems will be better than the tradition data management systems | Toft et al. (2014) |
| *Perceived usefulness of BDA systems (PU)* | PU1 | Using the BDA systems enhances business operations effectiveness. | Bach, Čeljo, and Zoroja (2016) |
| | PU2 | Using the BDA systems increases business productivity | Bach et al. (2016) |
| | PU3 | Using the BDA systems improves business performance | Bach et al. (2016) |
| *Perceived ease of use of BDA systems (PEU)* | PEU1 | Implementation process of BDA systems is understandable | Terzis et al. (2013) |
| | PEU2 | It is easy to integrate BDA systems with existing solutions | Terzis et al. (2013) |
| *Beliefs in the benefits of BDA systems (BNEB)* | BENB1 | My management team believes in the project benefits | Amoako-Gyampah and Salam (2004) |
| | BENB2 | My peers believe in the benefits of the new system | Amoako-Gyampah and Salam (2004) |
| | BENB3 | I believe in the benefits of the NEW system | Amoako-Gyampah and Salam (2004) |
| *Perceived BDA system quality (SQ)* | SQ1 | BDA systems provide information in timely manner | Shin (2015a, 2015b) |
| | SQ2 | BDA systems make information very accessible to companies. | Shin (2015a, 2015b) |
| | SQ3 | BDA systems can flexibly adjust to new demands and conditions. | Shin (2015a, 2015b) |
| *Perceived information quality (IQ)* | IQ1 | Information available from BDA systems is reliable. | Zheng et al. (2013) |
| | IQ2 | Information available from BDA systems are accurate | Zheng et al. (2013) |
| | IQ3 | BDA systems can provide information from huge volume of data. | Zheng et al. (2013) |

**Table 2**
Characteristics of the respondents and organisations ($n$ = 150).

| Variables | Values | Frequency | Percentage (%) |
|---|---|---|---|
| *Role in organisation* | CEO/COO/CIO/CFO | 24 | 15.9% |
| | V.P., General Manager, etc. | 38 | 25.7% |
| | Director, Controller, etc. | 40 | 26.6% |
| | Manager, Senior Analyst, etc. | 48 | 31.8% |
| *Number of employees* | ≤250 | 36 | 24.1% |
| | 400–800 | 40 | 26.8% |
| | >800 | 74 | 49.1% |
| *Turnover (in millions INR)* | Turnover ≤ 750 | 22 | 14.5% |
| | 750 < Turnover ≤ 3000 | 42 | 27.9% |
| | Turnover > 3000 | 86 | 57.6% |

### 4.3. Results

The research model of the study was tested using the Partial Least Square (PLS) method, using the software application Smart PLS 3.0 (Hair, Ringle, & Sarstedt, 2011). PLS method was preferred because it enables modelling latent constructs under the condition of non-normality and is appropriate for small to medium sample sizes (Chin, Marcolin, & Newsted, 2003; Hair et al., 2011). The evaluation of the model according to the PLS method follows a two-stage process (Chin, 2010). The first stage includes the evaluation of the measurement model by examining the reliability and the convergent and discriminant validity of the constructs. The second stage includes evaluation of the structural model by testing the significance of the relationships between the model constructs.

#### 4.3.1. The measurement model

Table 3 depicts the mean, standard deviation, Cronbach's Alpha, Composite Reliability and Average Variance Extracted values for all the constructs of the model. To indicate reliability, the Cronbach's alpha scores should exceed the recommended value of 0.60 and composite reliability scores should exceed the recommended value of 0.7 (Nunnally & Bernstein, 1994). Cronbach's alpha value of perceived usefulness is 0.587 that is below the recommended value of 0.6. Cronbach's alpha assumes that all indicators are equally reliable, while PLS prioritizes the indicators according to their individual reliability. Therefore, it is more appropriate to apply a different measure of internal consistency reliability (e.g. composite reliability) then Cronbach's alpha in PLS (Hair, Hult, Ringle, & Sarstedt, 2016). In order to assess discriminant validity, average variance extracted was used to measure the average variance shared between a construct and its measures (Fornell & Larcker, 1981). The average variance extracted of a construct should be greater than the variance shared between the construct and other constructs in the research model (i.e., the squared correlation between two constructs). Therefore, the square root of average variance extracted should be greater than the inter-correlations in the corresponding rows and columns for adequate discriminant validity (Zheng et al., 2013). As indicated in Table 3, the square root of average variance extracted of all constructs was greater than the corresponding inter-construct correlations.

**Table 3**
Mean, standard deviation, inter-correlations and reliability scores. The diagonal (in bold) shows the square roots of the average variance extracted.

| Construct | Mean | SD | CA | CR | AVE | ATT | BI | BNEB | IQ | PEU | PU | SQ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ATT | 3.93 | 0.89 | 0.806 | 0.911 | 0.836 | **0.914** | | | | | | |
| BI | 4.31 | 0.79 | 0.888 | 0.947 | 0.899 | −0.016 | **0.948** | | | | | |
| BNEB | 3.5 | 0.76 | 0.678 | 0.812 | 0.591 | 0.189 | 0.180 | **0.769** | | | | |
| IQ | 3.62 | 0.87 | 0.742 | 0.852 | 0.659 | 0.238 | 0.237 | 0.543 | **0.812** | | | |
| PEU | 3.79 | 0.96 | 0.835 | 0.923 | 0.857 | −0.109 | 0.316 | −0.044 | −0.085 | **0.926** | | |
| PU | 3.82 | 0.75 | 0.587 | 0.754 | 0.509 | 0.615 | 0.258 | 0.309 | 0.264 | 0.102 | **0.713** | |
| SQ | 3.73 | 0.82 | 0.821 | 0.893 | 0.736 | 0.178 | 0.274 | 0.362 | 0.276 | 0.159 | 0.333 | **0.858** |

*Note:* SD = standard deviation, CA = Cronbach's alpha, CR = Composite reliability and AVE = Average variance extracted.

Convergent validity is the degree to which individual indicators reflecting a construct converge in comparison to indicators measuring different constructs. Fornell and Larcker (1981) proposed average variance extracted as a commonly applied criterion of convergent validity. An average variance extracted value of 0.500 or more indicates that a construct explained more than half of the variance of its items and, thus, proves sufficient convergent validity. All average variance extracted, presented in Table 3, ranged from 0.51 to 0.89, higher than the cut-off value of 0.500. In addition, all the factor loadings and their corresponding t-values, presented in Table 4, exceeded 0.7 and 1.96 ($P < .05$), respectively, thereby demonstrating adequate convergent validity (Table 5).

### *4.3.2. The structural model*

The test of the structural research model included estimates of the path coefficients. Path coefficients indicate the strengths of relationships between the independent and dependent variables, whereas the $R^2$ value denotes the extent to which the independent variables explain the observed variance. The path coefficients along with the $R^2$ value (significance and loadings) obtained in this study indicated the extent to which data supported the hypothesised research model (Fig. 2).

Fig. 2 depicts results of the test of the hypothesised research model. All the paths specified in TAM were significant. These paths included direct and indirect effects of ease of use, usefulness, and attitude toward adoption intention, accounting for 42.5% of the variance in intention. As predicted, beliefs in the benefits of BDA systems had a significant influence on perceived usefulness and accounted for 30.9% of the variance in perceived usefulness. However, belief in the benefits of BDA systems did not influence perceived ease of use. As expected, information quality and system quality had a significant influence on belief in the benefits of BDA systems, and they accounted for 54.4% of the variance. Further, the hypothesis was tested by examining the structural model including estimates of the path coefficients and t-values using Smart PLS software. Results of the structural model are summarised in Table 6 and Fig. 2.

### *4.3.3. The mediation effect*

This section demonstrates the mediation effect of BNEB, perceived usefulness and perceived ease of use on attitude. This research study uses the method of Baron and Kenny (1986) for testing the mediation. Following steps of testing mediation were used in this study (Al-Jabri and Roztocki, 2015). The mediation of perceived usefulness was tested first (a = constant term and b, c, d = regression coefficient):

**Table 4**
Factor loading.

| Constructs | Item | Load | *T*-value |
|---|---|---|---|
| *Behavioral intension to use BDA systems (BI)* | BI1 | 0.942 | 8.535 |
| | BI2 | 0.954 | 8.653 |
| *Attitude toward BDA systems (ATT)* | ATT1 | 0.894 | 33.055 |
| | ATT2 | 0.934 | 53.396 |
| *Perceived usefulness of BDA systems (PU)* | PU1 | 0.788 | 3.886 |
| | PU2 | 0.742 | 3.786 |
| | PU3 | 0.696 | 2.448 |
| *Perceived ease of use of BDA systems (PEU)* | PEU1 | 0.940 | 10.775 |
| | PEU2 | 0.912 | 9.348 |
| *Beliefs in the benefits of BDA systems (BNEB)* | BENB1 | 0.763 | 10.734 |
| | BENB2 | 0.792 | 8.897 |
| | BENB3 | 0.750 | 7.621 |
| *BDA system quality (SQ)* | SQ1 | 0.834 | 18.660 |
| | SQ2 | 0.860 | 25.546 |
| | SQ3 | 0.878 | 26.990 |
| *BDA information quality (IQ)* | IQ1 | 0.848 | 29.920 |
| | IQ2 | 0.741 | 11.262 |
| | IQ3 | 0.843 | 16.660 |

**Table 5**
Results of hypotheses testing.

| Hypothesis | Path | Coefficient | *T*-value | *P*-value | Significance | Support |
|---|---|---|---|---|---|---|
| H1 | ATT → BI | 0.281 | 2.434 | 0.022 | 0.05 | Yes |
| H2 | PU → BI | 0.430 | 3.179 | 0.001 | 0.01 | Yes |
| H3 | PU → ATT | 0.632 | 3.639 | 0.000 | 0.01 | Yes |
| H4 | PEU → PU | 0.116 | 1.016 | 0.301 | n.s | No |
| H5 | PEU → ATT | 0.173 | 2.052 | 0.051 | 0.1 | Yes |
| H6 | BNEB → PU | 0.314 | 3.158 | 0.001 | 0.01 | Yes |
| H7 | BNEB → PEU | 0.044 | 0.416 | 0.695 | n.s | No |
| H8 | IQ → BNEB | 0.480 | 5.719 | 0.000 | 0.01 | Yes |
| H9 | SQ → BNEB | 0.230 | 2.701 | 0.009 | 0.01 | Yes |

$P < .1$ 1.652.
$P < .05$ 1.971.
$P < .01$ 2.599.
*Note:* BI = Behavioral intension to use BDA systems; ATT = Attitude toward BDA systems; PU = Perceived usefulness of BDA systems; PEU = Perceived ease of use of BDA systems; BNEB = Beliefs in the benefits of BDA systems; SQ = BDA system quality; IQ = BDA information quality.

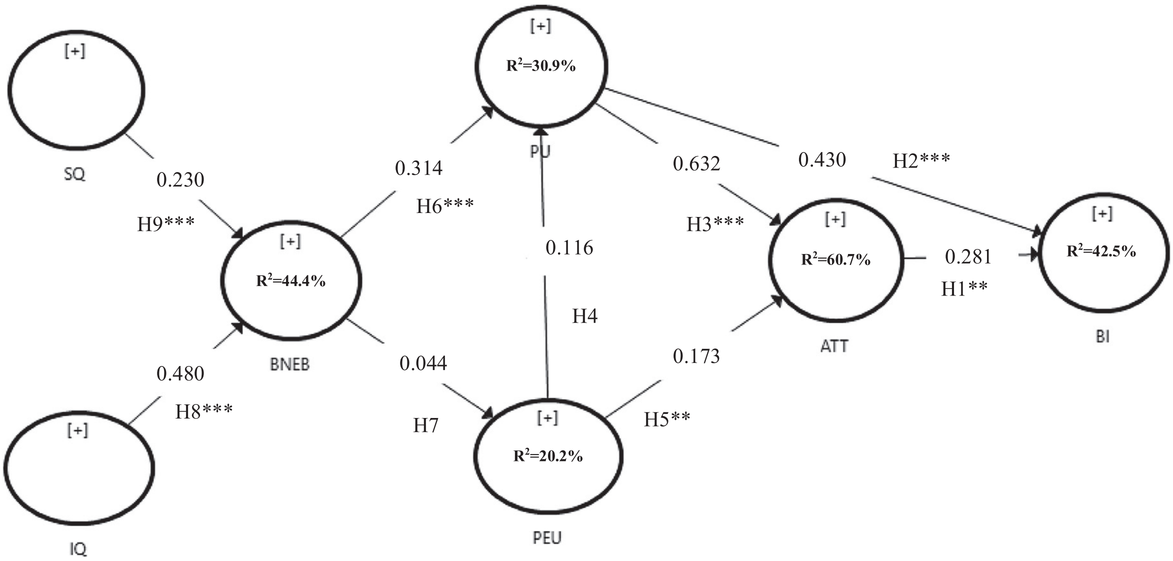


**Fig. 2.** Path coefficients and $R^2$ of the endogenous variables.
*Note:* BI = Behavioral intension to use BDA systems; ATT = Attitude toward BDA systems; PU = Perceived usefulness of BDA systems; PEU = Perceived ease of use of BDA systems; BNEB = Beliefs in the benefits of BDA systems; SQ = BDA system quality; IQ = BDA information quality.

- ***Step 1:*** It indicated that the independent variables (i.e., system quality and information quality) were correlated with the mediating variable (i.e., benefits of BDA systems)
  *1.a.* BNEB = *a* + *b(system quality)* *(Model 1)*
  *1.b.* BNEB = *a* + *b (information quality)* *(Model 2)*

- ***Step 2:*** It indicated that the mediating variable (BNEB) affects the dependent variable (i.e., PU), controlling the independent variables (i.e., SQ and IQ).
  *2.a. Perceived usefulness = a + b(*BNEB*) + c(system quality)* *(Model 3)*
  *2.b. Perceived usefulness = a + b(*BNEB*) + c(information quality)* *(Model 4)*

- ***Step 3:*** It indicated that the mediating variables (i.e., BNEB and perceived usefulness) affect the dependent variable (i.e., attitude), controlling the independent variable (i.e., system quality and information quality)
  *3.a. Attitude = a + b(perceived usefulness) + c(*BNEB*) + d(system quality)* *(Model 5)*
  *3.b. ATT = a + b(perceived usefulness) + c(*BNEB*) + d(information quality)* *(Model 6)*

The above-mentioned three steps were repeated to test the mediation effect of perceived ease of use:

- ***Step 4:*** Same as in Step 1 above.
- ***Step 5:*** It indicated that the mediating variable (BNEB) affects the dependent variable (i.e., PEU), controlling the independent

**Table 6**
Testing the mediation effects of BNEB, PU and PEU.

| Model | DV[a] | IV[b] | B | SE | *T*-value | *P*-value | Adj. $R^2$ | F |
|---|---|---|---|---|---|---|---|---|
| 1 | BNEB | SQ | 0.358 | 0.084 | 4.272 | 0.000 | 0.123 | 22.9 |
| 2 | BNEB | IQ | 0.571 | 0.052 | 11.066 | 0.000 | 0.322 | 32.7 |
| 3 | PU | SQ | 0.348 | 0.092 | 3.801[c] | 0.175 | 0.164 | 10.1 |
| | | BNEB | 0.212 | 0.092 | 2.353 | 0.000 | | |
| 4 | PU | IQ | 0.546 | 0.061 | 8.927[c] | 0.105 | 0.293 | 9.9 |
| | | BNEB | 0.270 | 0.144 | 1.881 | 0.000 | | |
| 5 | ATT | SQ | 0.355 | 0.089 | 4.001[c] | 0.412 | 0.120 | 34.2 |
| | | BNEB | 0.214 | 0.099 | 2.161 | 0.147 | | |
| | | PU | 0.642 | 0.082 | 7.832 | 0.000 | | |
| 6 | ATT | IQ | 0.558 | 0.053 | 10.485[c] | 0.476 | 0.472 | 36.4 |
| | | BNEB | 0.195 | 0.123 | 1.585 | 0.109 | | |
| | | PU | 0.690 | 0.057 | 12.155 | 0.000 | | |
| 7 | PEU | SQ | 0.358 | 0.087 | 4.132[d] | 0.032 | 0.122 | 5.2 |
| | | BNEB | −0.082 | 0.120 | 0.685 | 0.000 | | |
| 8 | PEU | IQ | 0.577 | 0.053 | 10.985[d] | 0.009 | 0.329 | 7.8 |
| | | BNEB | −0.029 | 0.213 | 0.213 | 0.000 | | |
| 9 | ATT | SQ | 0.358 | 0.085 | 4.189[d] | 0.023 | 0.017 | 8.1 |
| | | BNEB | −0.083 | 0.133 | 0.614[d] | 0.032 | | |
| | | PEU | −0.152 | 0.137 | −1.115 | 0.000 | | |
| 10 | ATT | IQ | 0.577 | 0.051 | 11.386 | 0.286 | 0.018 | 12.7 |
| | | BNEB | −0.029 | 0.125 | 0.228[c] | 0.819 | | |
| | | PEU | −0.155 | 0.145 | 1.069 | 0.000 | | |

*Note:* BI = Behavioral intension to use BDA systems; ATT = Attitude toward BDA systems; PU = Perceived usefulness of BDA systems; PEU = Perceived ease of use of BDA systems; BNEB = Beliefs in the benefits of BDA systems; SQ = BDA system quality; IQ = BDA information quality.

[a] Dependent variable.

[b] Independent variable.

[c] Full mediation.

[d] Partial mediation.

variables (i.e., system quality and information quality).

*5.a. Perceived ease of use = a + b(*BNEB*) + c(system quality)* *(Model 7)*

*5.b. Perceived ease of use = a + b(*BNEB*) + c(information quality)* *(Model 8)*

- ***Step 6:*** It indicated that the mediating variables (i.e., BNEB and PEU) affect the dependent variable (i.e., ATT), controlling the independent variable (i.e., SQ and IQ)

  *6.a. Attitude = a + b(perceived ease of use) + c(*BNEB*) + d(system quality)* *(Model 9)*

  *6.b. Attitude = a + b(perceived ease of use) + c(*BNEB*) + d(information quality)* *(Model 10)*

Table 6 demonstrated the results of the regression analysis of the above ten models. Models 1 and 2 depict that independent variables system quality and information quality significantly affect the mediating variable BNEB. Models 3 and 4 indicate that system quality and information quality, along with BNEB, significantly affect the dependent variable perceived usefulness, indicating that BNEB partially mediates the relationship between system characteristics (i.e., system quality and information quality) and perceived usefulness. Similarly, models 5 and 6 indicate that system characteristics (system quality and information quality), along with BNEB and perceived usefulness, significantly affect the dependent variable attitude, indicating that BNEB and perceived usefulness partially mediate the relationship between system characteristics (i.e., system quality and information quality) and attitude. Models 7, 8, 9 and 10 depict that, after including the mediating variable BNEB, perceived ease of use, the system characteristics (i.e., system quality and information quality) are no longer affecting perceived ease of use and attitude, respectively. This ascertains that BNEB fully mediates the relationship between system characteristics (i.e., system quality and information quality), perceived ease of use, system characteristics (i.e., system quality and information quality) and attitude.

## 5. Discussion

The findings of this research study provide a preliminary test of the viability of the research model within the context of BDA systems. In this study, the extended TAM model was tested in the context of BDA implementation. This research contributes to information system adoption literature by considering a new belief construct, which reflects on the understanding of the benefits of a new information system (i.e., the BDA system) among the users in firms. This study extends the TAM model by adding a belief construct (perception of benefits of a BDA systems) and two external variables (system quality and information quality), as recommended by Liao and Tsou (2009) and Al-Jabri and Roztocki (2015). The findings strongly supported the appropriateness of using TAM to understand the factors influencing the adoption of BDA systems in Indian firms. This research study contributes to the body of knowledge by considering two important and recognised factors in information system research, i.e., system quality and information quality. These two constructs are external factors, which affect the core TAM constructs through the user belief in the benefits of BDA system. This study also contributes by investigating and testing existing IT theory in a new information system context, i.e., the implementation of BDA systems. Unlike many information systems, BDA systems require simultaneous changes in information sharing methods (Constantiou & Kallinikos, 2015). Therefore, firms need to change their business processes and information system usage, which makes implementation of BDA a challenging task (Chen et al., 2015).

Among all the proposed hypotheses, the strongest relationship was the impact of IQ on BNEB. The results of this study are consistent with several previous studies (Ji-fan Ren et al., 2016; Kuo & Lee, 2009). Mostly, the purpose of information system implementation is to enhance operational management and work performance. BDA systems not only improve job performance or productivity but also provide real-time insights for decision-making. According to DeLone and McLean (1992), information quality and system quality are important in building a successful information system. Information quality plays a key role in providing and obtaining the information of customers and markets, which further leads to the formation of shared beliefs among organisational participants, especially among the targeted users of an innovation (Kwon et al., 2014), as found in this study. System quality allows users to explore the BDA systems' technical and functional perspective (Gandomi & Haider, 2015). It allows users to retrieve information and explore the perceived usefulness of the BDA systems (Tate et al., 2014). System quality helps in the formation of BNEB and, thus, affects perceived usefulness (Shin, 2015a, 2015b).Therefore, this study introduced information quality and system quality as potential variables to further understand the benefits associated with the BDA systems. Basically, the purpose of BDA systems is to accumulate a large amount of structured and unstructured data for real-time, strategic, tactical and operational decision-making (Chen & Zhang, 2014). Therefore, timeliness, accessibility, accuracy, reliability and completeness of information are critical concerns with BDA systems (Ji-fan Ren et al., 2016). If the insights or information provided by BDA systems are not provided in time, incomplete or in accurate, then business managers of firms do not realise the benefits associated with BDA systems. Specifically, users' perception of benefits of BDA systems influence the characteristics of BDA systems. BDA system users require high information and system quality in order to ensure that the information can be captured and made available in real time to accomplish their specific tasks. Higher quality information provided by BDA systems lead to better outcomes and increases the perception that BDA systems could create value to firms.

BNEB is a significant determinant that directly affects perceived usefulness. When business managers and top management of firms are satisfied with the benefits of BDA systems, their appreciation regarding perceived usefulness of BDA systems will obviously be higher. This finding is consistent with the work of Kuo and Lee (2009). However, BNEB does not affect perceived ease of use of BDA systems among business managers of Indian firms. This outcome is inconsistent with the findings of Amoako-Gyampah and Salam (2004). Despite all the benefits that BDA systems could provide, managers might not find BDA systems user-friendly and easy to use. Therefore, they would not feel comfortable using BDA systems. BNEB allows their users to understand the different ways in which BDA systems will make their firms productive (Dubey et al., 2016). However, in this study, BNEB was found to fully mediate the relationship between system characteristics (i.e., system quality and information quality) and perceived usefulness, which means that BNEB does not reduce the uncertainty about the usefulness of the BDA systems in day-to-day routine. In the BDA environment, users are more concerned with how BDA information and system quality are actually useful to firms. Such users would support business processes irrespective of their management and peer perception in the benefits of BDA systems. This study found that perceived ease of use affects the formation of attitude. BNEB partially mediates the relationship between system characteristics (i.e., system quality and information quality) and perceived ease of use. These findings were consistent with others and demonstrate that perceived ease of use has a significant impact on attitude towards a new innovation (Gangwar et al., 2015). This result implies that it is crucial for business managers in India to understand their management system as well as peer-perception towards BDA systems because it would shape their attitude towards using the technology. This result can be explained by the fact that system quality and information quality of BDA systems would help in developing a positive perception towards the benefits of BDA systems among business managers and management of Indian firms. Due to a positive perspective regarding the benefits of BDA systems, business managers could further perceive that using BDA systems would be free of added effort.

Perceived ease of use of BDA systems influenced behavioural intention indirectly through attitude. This result is consistent with the study of Kuo and Lee (2009).In other words, if business managers of Indian firms are finding it difficult to work with BDA systems they are quite likely to use other alternatives (i.e., the traditional business intelligence) rather than BDA systems. Therefore, firms should provide an easily understandable interface and solutions that should be easily integrated with the existing applications used by Indian business managers in order to encourage them to adopt the BDA systems. However, perceived ease of use had an insignificant effect on perceived usefulness (H4). This finding is consistent with the work of Amoako-Gyampah and Salam (2004) but inconsistent with several prior research works (Ayeh et al., 2013; Liao & Tsou, 2009; Bruner & Kumar, 2005; Van der Heijden, 2004). The result indicated that the ease of use related to BDA systems does not create a positive perception towards the usefulness of BDA systems. This means that although BDA systems could be easy to use, business managers do not recognise its usefulness. This may be explained by the observation that the users of BDA systems are more concerned with the larger goal of how a BDA system supports business processes rather than how they support technology itself. Therefore, the effort of BDA system providers for making it easier to use does not lead to creating belief in the usefulness of BDA systems. Perceived usefulness of BDA systems had a strong influence on attitude and behavioural intention towards BDA systems. This result is consistent with the study of Lin et al. (2011). The result indicated that business managers of Indian firms believe that the use of the BDA systems would help them form a positive attitude in using BDA systems and which results in their increased intention to use BDA. A possible explanation for this finding came from the fact that business managers who perceived that using BDA systems was useful also intended to use the systems more frequently.

This study demonstrated that the impact of beliefs formed regarding the usefulness of the BDA system was significant in shaping a positive attitude towards the BDA system. If top management of a firm takes suitable steps to positively influence the belief structures then it will assuredly facilitate positive attitude formation. This will, in turn, lead to increased acceptance of the BDA technology by firm managers (Hu, Dinev, Hart, & Cooke, 2012). One mechanism for influencing BNEB is through improved system quality as part of the BDA implementation. The study found that system quality influenced the formation of BNEB, though BNEB influenced only perceived ease of use. This finding is important and significant as it provides business managers a tool (system characteristics) to positively influence the formation of BNEB, and in turn, affecting behavioural intention. By providing appropriate system quality, business managers can influence the formation of beliefs regarding the perceived ease of use and BNEB (Afshari & Peng, 2015). The results demonstrate that if business managers put good system quality in place, the system characteristics are likely to have a positive effect on the BNEB, which would eventually lead to an increase in the acceptance of BDA systems. Although business managers have recognised the importance of system quality in BDA implementation (Chae, 2015), this research study provided both empirical and theoretical support for why system characteristics are important.

By adopting BDA, firms could comprehend customer needs in elaborate detail as with mobile platforms and Internet of Things, BDA can capture data on the customer 24/7, and with a 360-degree perspective. Thus, firms can understand the requirements of the customer (both felt and unfelt needs) ahead of their competitors who have not adopted BDA. Firms that have adopted BDA ahead of their competitors could launch new products and services as well as modify existing ones, and focus on mass customisation, improved marketing, and sales and after-sales services. This will result in the firms securing new customers while retaining existing ones, adding value to the firm. Though the adoption of BDA would initially entail investment, over a period of time, it would reduce operational costs, by preventing the maintenance of machines, streamlining of supply chain management, forecasting demand, increasing energy efficiency, shifting to lean manufacturing and stimulating new manufacturing processes (Verma, 2017).

It can be argued that BDA could uncover large hidden values from diverse, massive and complex datasets (Gandomi & Haider, 2015). Thus, this study helps firm managers who are trying to create value from BDA by providing insights into the extension of information system adoption model. It highlights the importance of system characteristics in BDA for creating the right perspective regarding the benefits of BDA and its adoption. This would finally lead to value creation from new innovations like BDA. System and information quality perspectives highlight the importance of insights in the adoption of BDA and helps firm to create data economy for value creation and enhanced firm performance. The study findings could provide a useful roadmap to firm managers who are trying to create value from BDA by identifying and solving the issues pertaining to system characteristics and perception towards BDA systems. The findings on adoption intention of BDA and its antecedents (i.e., perceived ease of use, perceived usefulness, BNEB, information quality and system quality) will facilitate the scalability of BDA. The findings also suggest that business managers who are trying to capture the value from BDA should consider information quality, BNEB, perceived usefulness and perceived ease of use as important strategic objectives to ensure improved adoption intention and ultimately improve firm performance.

## 6. Conclusion

This research study extends the TAM model by adding one belief construct (i.e., perception of benefits of a BDA system) and two external variables (i.e., system quality and information quality). Orlikowski and Iacono (2001) criticised previous TAM studies because TAM lacked the means for explanations of contextual and temporal variations. Therefore, it was deemed necessary to theorise, in more detail, about differences in IT artefacts and their use and role in different contexts (Gangwar et al., 2015). This study helps to leverage the rich research available in the domain of technology acceptance literature by integrating factors like belief in benefits of an innovation with the TAM model. The empirical results provide strong evidence to support the proposed research model as five of the seven postulated relations were shown to be significant. Consistent with previous research studies in the field of technology adoption, perceived usefulness has a positive influence on attitude and behavioural intention. While perceived ease of use has a positive impact on attitude, the effect of perceived ease of use on perceived usefulness is not significant. This suggests that the ease of use related to BDA systems does not create a positive perception towards the usefulness of BDA systems. Specific emphasis has been placed on the effect of system characteristics (system quality and information quality) and attitude. Firstly, this study demonstrates that perceived usefulness and BNEB fully mediate the effect between system characteristics. Secondly, this study demonstrates that perceived ease of use and BNEB partially mediate the effect between system characteristics. Thus, with regard to the findings of Yang, Lu, Gupta, Cao, and Zhang (2012), who found BNEB to have high relevance for an IT application adoption, this study can add that BNEB is also relevant to the formation of perception of ease of use as it mediates the relationship between system characteristics and perceived ease of use. The important extension of the TAM model provides the conceptual understanding of the differences between beliefs and attitudes towards adoption intention.

### 6.1. Implications for practice

Business managers may have several ways to improve BDA systems, but the insights from this study would help them to improve system adoption decision. The intention to adopt BDA was higher among business managers who believed in the benefits of BDA systems and decided to take immediate steps to improve the quality of the BDA system and information quality. The research model provides a mechanism for understanding and assessing the relative influence of information and system characteristics, which provides important guidance to BDA system designers. If users of the BDA system perceive problems with the accuracy of BDA information as a critical factor, then the designers can channelize their efforts accordingly. Knowledge about the relative influences of factors will become a basis for the creation of design guidelines and standards of building effective BDA systems. Furthermore, the proposed research model has diagnostic value at any stage of BDA system's implementations. BDA systems are most likely to be built from scratch, rather than being evolved. BDA systems typically require IS architectural modifications over time and addition of new applications to meet unique business needs.

### 6.2. Implications for research

The implications of this study for research are manifold. In order to understand the influence of a system and its implementation attributes on beliefs, it is important to measure a set of beliefs and attitudes about the information system and its characteristics (Amoako-Gyampah & Salam, 2004). Furthermore, the aptness of research models should not be based only on the direct relationship of these factors with the intention of adoption or measures of business value (Wu et al., 2011). Such relationships could be better understood by examining suitable mediating factors related to beliefs and attitudes, such as usefulness, ease of use, beliefs, attitude and behavioural intention, as specified in TAM (Al-Jabri & Roztocki, 2015).

Comparative studies are required to describe the operationalisation and conceptualisation of the constructs to avoid mixing research studies, which examine factors at different levels of abstraction (Liao & Tsou, 2009). Insights from such studies would contribute to the field (Liao & Tsou, 2009). Several previous research studies have persistently extended TAM (Fig. 1) (Cheung & Vogel, 2013; Dutot, 2015; Gangwar et al., 2015). This study, however, investigated the effects of the information system artefact as antecedents to system characteristics (i.e., information and system quality), BNEB, perceived usefulness and perceived ease of use and related factors in the context of BDA. This research study has as curtained the features that make one information system more useful, easy to use or relevant as compared to other options. The proposed research model provides a platform for more detailed theorising and testing of such ideas. It confirms the absolute importance of components of the integrated model. Identification and testing of alternative models develops an approach for predicting and understanding mediating effect of different factors.

### 6.3. Limitations and future research

BDA implementations have been affected by several challenges and, therefore, there is a compelling need to conduct more directed research toward creating a set of guidelines for assured BDA system implementation success. This study found encouraging results on the role of external factors such as BDA system and information quality and the mediation effect of beliefs in benefits of BDA systems, perceived usefulness on attitude and attitude on the behavioural intention.

The limitations of the present research effort include restricted focus on a single technology (BDA) within a single nation (India), apart from a relatively small sample size. Besides, these results may not be extrapolated to other IT applications (e.g. cloud computing) where usage is voluntary. However, these limitations are significant given that they may fuel future research in this direction. Further research may examine the opportunity of enhancing the model by integrating it with the theories about users' satisfaction (e.g. the stakeholder theory or the Yield Shift Theory of Satisfaction) (Briggs, Reinig, & de Vreede, 2008). This could help in understanding the individual's perception about the adoption of BDA in a mandatory use setting. This research is one of the first information system studies to examine system characterises and BNEB. However, more efforts are needed to validate the construct of this study theoretically and methodologically.

The sampling method (i.e., convenience sample) introduced a potential bias in this study, although participants in this study were from various regions of India. Hence, the results may not be generalizable to a broader business manager population. Future studies should take a random sample from across India. Although this research study was specifically conducted in firms implementing several modules of a BDA system, it is only prudent that caution be exercised in generalising the findings. Also, there were other factors besides system and information quality and BNEB, such as the nature of the technology itself, which impacted behavioural intention. When a BDA system is adopted, firm business managers must learn to overcome the extant knowledge barriers, acquire complex new knowledge and adopt new organisational structures so that implementation of the new technology becomes a success (Demirkan & Delen, 2013). Research efforts in the past have been devoted to adding extensions to the theory by examining the antecedents of the two beliefs constructs underlying TAM. As noted by Venkatesh and Davis (2000), a better understanding of these would enable us to design effective organisational interventions that might lead to increased user acceptance and use of new information systems.

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