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Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness

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ABSTRACT

The data-centric revolution generally celebrates the proliferation of business analytics and AI in exploiting firm's potential and success. However, there is a lack of research on how the unintended consequences of AI integrated business analytics (AI-BA) influence a firm's overall competitive advantage. In this backdrop, this study aims to identify how factors, such as AI-BA opacity, suboptimal business decisions and perceived risk are responsible for a firm's operational inefficiency and competitive disadvantage. Drawing on the resource-based view, dynamic capability view, and contingency theory, the proposed research model captures the components and effects of an AI-BA opacity on a firm's risk environment and negative performance. The data were gathered from 355 operational, mid-level and senior managers from various service sectors across all different size organisations in India. The results indicated that lack of governance, poor data quality, and inefficient training of key employees led to an AI-BA opacity. It then triggers suboptimal business decisions and higher perceived risk resulting in operational inefficiency. The findings show that operational inefficiency significantly contributes to negative sales growth and employees' dissatisfaction, which result in a competitive disadvantage for a firm. The findings also highlight the significant moderating effect of contingency plan in the nomological chain.

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1. Introduction

> Artificial intelligence (AI) is doing a lot of good and will continue to provide many benefits for our modern world, but along with the good, there will inevitably be negative consequences. The sooner we begin to contemplate what those might be, the better equipped we will be to mitigate and manage the dangers. Marr (2021)

Generation and processing of data in this age of data deluge have taken a revolutionary shape due to the combined effects of big data, analytics, and artificial intelligence (AI) (Mikalef & Gupta, 2021; Vidgen et al., 2017). The momentum of big data and business analytics (BA) is increasing at an unprecedented manner due to the arrival of AI (Conboy et al. 2020; Davenport & Malone, 2021). Researchers grapple with the challenges of how to leverage AI integrated BA for the creation of business values that would supplement competitive advantage (Davenport, 2018; Sharda et al., 2016). We define an AI integrated BA (AI-BA) solution as the analytical insights provided by intelligent machines and augmented by both machines and humans to make meaningful decisions (e.g., portfolio/wealth management recommendations in banks) (Davenport & Ronanki, 2018). AI takes analytics to the next level in developing and testing models with increased automation and sophistication (Davenport, 2018). AI-BA solution helps firms manage the growing volumes of data from the various sources, breaks those data into manageable and meaningful insights, which helps managers take appropriate decision on a day-to-day basis (Bichler et al., 2017; Côrte-Real et al., 2019; Cosic et al., 2015; Hindle & Vidgen, 2018; Popovič et al., 2018). However, poor governance and data quality may result in incorrect decisions and competitive disadvantages (Ghasemaghaei, 2019; Tallon 2013). Yet, inappropriate AI integrated BA literature in information systems (IS) is very sparse (Agarwal & Dhar, 2014; Davenport, 2018; Lycett, 2013; Doyle & Conboy, 2020; Grover et al., 2018; Mikalef & Krogstie, 2020), challenging us to identify the factors relevant to AI-BA opacity and its effects on operational inefficiency and competitive disadvantage (Ghasemaghaei & Turel, 2021).

In the AI-BA solution, various data (e.g., web, social media, mobile devices, sensor networks) are fed from different sources (Müller et al., 2017). The system developers ensure that these data are valuable, usable, and curated. This is appropriate data. The AI-BA solution analyses these data and provides some outputs with recommendations. The employees of the firm need to understand these outputs provided by the AI-BA solution (Paschen et al., 2020). With their

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understanding, the employees are needed to select which output they need to take up with priority. Proper training is to be imparted to the employees of the firms to improve their level of understanding and absorptive capacity for the selection of the right and appropriate outputs (Maity, 2019). With regard to inappropriate data, Tse et al. (2020) (p. 3)

> AI-driven systems and models will stop functioning when being fed wrong and malformed data. Furthermore, the speed they can run at is bound to diminish when they have to ingest a large amount of data. These problems will, at best, slow the entire system down and, at worst, bring it to its knees.

As such, an AI-BA opacity might adversely affect a firm's operational efficiency impairing competitive advantage (Conboy et al., 2020; Sun & Pang, 2017). To ensure the feeding of appropriate data to the system, proper governance is to be ensured. Appropriate governance is considered a robust framework that would help to ensure measurable and expected results (Winter & Davidson, 2019). However, a little attention has been paid to the role of data governance and its influence to develop an appropriate AI integrated BA (Tallon 2013).

Although big data analytics has been widely studied in the context of IS with regard to big data investments (Agarwal & Dhar, 2014; Grover, Chiang, Liang, & Zhang, 2018), information sources (Chen et al., 2012), big data infrastructure (Goes, 2014), information value chain (Abbasi et al., 2016), firm performance (Akter et al., 2016; Wamba et al., 2017) and innovation capabilities (Mikalef & Krogstie, 2020), there are a few studies that have explored an AI-BA opacity and its salient negative consequences, such as operational inefficiency, employee's dissatisfaction and firm's competitive disadvantages (Ghasemaghaei & Turel, 2021). When viewed macroscopically, the contributions of such technology along with huge data may quite often fail and invite an imbalance in information systems (Zuboff, 2015). This critical reflection on the unintended consequences of an AI-BA opacity has motivated us to identify the factors that might cause operational inefficiency, negative sales growth, employee's dissatisfaction, and a competitive disadvantage. To fill up this gap, the study puts forward the following research questions:

RQ1: What are the components and effects of an AI-BA opacity?

RQ2: Is there any moderating effect of contingency plan between suboptimal business decision and operational inefficiency and perceived risk and operational inefficiency of a firm?

To answer these research questions, we integrate a few theoretical streams. First, we argue that an AI-BA opacity is reflected by a lack of data governance capability, poor data quality, and inefficient training capabilities. This conceptualisation is rooted in the resource-based view and dynamic capabilities of the firm, which highlights that inappropriate capability (e.g., AI integrated BA) may contribute to competitive disadvantages (Conboy, 2020; Teece et al., 1997). We also extend the contingency theory by investigating how contingency plan coalesces with various analytics capabilities to influence risk perceptions and operational inefficiency (Pratono, 2016; Vroom & Jago, 1995). Based on 355 survey responses of AI integrated BA managers in India, we conceptualise and empirically validate the nomological model identifying the components and effects of an AI-BA opacity.

The remaining part of this article covers the literature review (i.e., Section 2) followed by theoretical background with the development of a conceptual model (i.e., Section 3). Section 4 presents the research methodology with discussing instrument and data collection strategy. Section 5 analyses the data and presents results. The next section (i.e., Section 6) discusses the key findings and presents theoretical contributions, implications for practice and limitations, and future research directions. Finally, Section 7 provides the conclusive remarks of this research.

2. Literature review

2.1. Technological advancement and business analytics

Studies reveal that due to unprecedented technological advancements, firms are becoming more innovative to effectively respond to customer needs with the help of information science (Sharda et al., 2016; Nam et al., 2019). Firms are adopting numerous applications of IS for processing available data sets, as are found in many other studies (Bichler et al., 2017; Sharma et al., 2014). For adding value to drive appropriate decisions for the business, the tools and techniques qualitatively as well as statistically analyse enormous volume of such data sets, which are together called business analytics (BA) (Delen & Zolbanin, 2018). In terms of the studies conducted by GE and Accenture, it has been revealed that 89% of the firms in the world believe that in the volatile market, they will not succeed if they do not adopt BA solution (Delen & Zolbanin, 2018). Thus, different studies (e.g., Mikalef & Gupta, 2021; Wamba-Taguimdje et al., 2020) have observed that, for achieving success, firms need to take the help new age technologies, such as AI and big data analytics to create and capture value (Li et al., 2021).

2.2. The emergence of AI integrated business analytics

AI refers to the science of training machines to act like humans by gathering and processing large amounts of data and identifying patterns using various technologies (SAS Insights, 2018). As a natural extension of analytics, AI integrated BA combines data and sophisticated analytics techniques, such as machine learning, neural networks and deep learning to collect, process, interpret, and learn from data to achieve diagnostic, descriptive, predictive, and prescriptive outcomes (Davenport & Ronanki, 2018; Kaplan & Haenlein, 2019). AI integrated BA is different from traditional business analytics as it learns from data without being programmed before and identifies rules and patterns using analytics techniques, such as machine learning or deep learning (Davenport, 2018; Mikalef & Gupta, 2021).

The extant literature identifies that the best way to use the data is to take the help of combined effects of BA and AI (Kersting & Meyer, 2018). Big data analytics and AI have simultaneously brought in revolutionary progress in the business ambience as is transpired in other studies (Vidgen et al., 2017). But there is evidence where it has been observed that the unintended and unexpected consequences of big data analytics with AI have threatened to hinder business values (Zuboff, 2015). Studies showed that inappropriate adoption of technology leads to suboptimal decisions that eventually impacts firm operational activities (Antunes et al., 2014; Ilyina et al., 2019). There are several studies that explored the impact of BA in business firms (Sharma et al., 2014; Troilo et al., 2016). Thus, different studies highlighted the contributions of AI integrated BA in the firms and revealed that flawed technological solution results in deterioration of operational efficiency of the firms due to faulty decision.

The extant literature identifies both the positive and negative effects of AI integrated BA on operational efficiency and employee empowerment (Krishnamoorthi & Mathew, 2018; Motamarri et al., 2020; Tse et al., 2020). In the macroscopic sense, the use of AI integrated BA solution in the firms is observed to have invited an imbalance in power (Zuboff, 2015). Proper governance is construed to be one of the basic components for the successful adoption of AI integrated BA solution in the firms (Krishnamoorthi & Mathew, 2018; Tallon, 2013; Paschen et al., 2020). Governance is conceptualised as a process that helps a firm to attain its goal by the accurate usage of the system. However, studies on how unintended impacts of the use of AI integrated BA solution may bring by the unexpected entry of AI in the firm settings are at a rudimentary stage (Rapp et al., 2020).

Again, it has been observed in several studies that imparting appropriate training to the employees of the firms concerning any new technology is considered a vital condition for successful technology solution (Dubey et al., 2019; Motamarri et al., 2020). Besides, the quality of data plays an important and effective role in developing any AI-based business solution, as is revealed in some other studies (Dubey et al., 2019). In a study, it has been made clear that governance of AI solution includes appropriate governance of data, training, and conducive system support along with the implementation of an effective contingency plan (Winter & Davidson, 2019).

Studies reflect that any wrong technology solution adopted by a firm enhances the probability of failure of business growth of the firm multiplying the risk factors (Marks, 2008). This risk may include many issues like technical risk, privacy risk as well as a security risk (Post & Kagan, 2006). Studies highlight that AI-BA opacity leads to suboptimal decisions affecting the competitive edge of the firms (Karabag et al., 2014), resulting in financial loss as well as overall operational degradation of the firms (Croom et al., 2018; Kuo et al., 2010).

Studies have transpired that many firms sustain a loss of competency because of operational deficiency regarding their business growth (Claro & Ramos, 2018). Studies reflect that the employees of the firms often become unsatisfied owing to operational weakness as well as wrong decision-making of the management of the firms, and this dissatisfaction of the employees of the firms has a direct effect on the market share of the firm leading to negative business growth (Rapp et al., 2020). Because of this, the firms may have to incur the loss of market competitiveness, as is found in other studies (Karabag et al., 2014; Sun & Pang, 2017).

3. Theoretical background, conceptual model, and hypotheses development

3.1. Theoretical background

In the context of the adoption of AI integrated BA solution in the firms, some important factors acting as predictors to AI integrated BA solutions should need to be nurtured. For this, the firms must have the appropriate abilities to utilise their resources to achieve a competitive advantage. In the perspective of dealing with the capabilities of the firms for the best usage of the resources in an appropriate way, we will discuss dynamic capability view (DCV) (Teece et al., 1997) with resource-based view (RBV) theory (Kor & Mahoney, 2003). RBV has been developed with the concept of developing abilities for utilisation of resources to achieve competitive advantage (Delen & Zolbanin, 2018; Gunasekaran et al., 2017). Dynamic capability (DC) is defined as "ability to integrate, build and reconfigure internal and external resources/competences to address and possibly shape rapidly changing business environments" (Teece, 2012, p. 1395). This is conceptualised with the sense of higher-order capability (Teece, 2014). The DCV has been considered as an extension of RBV. RBV helps to extract usable data from different sources. DCV, in addition, helps to extract such usable data that fits with the dynamic market (Teece, 2012; Eckstein et al., 2015).

Firms are to put full endeavour for developing the abilities towards best utilisation of the resources including use of curated data, which is the main theme of RBV and DCV. These theories highlight, for achieving better performance of the firms, the organisations must possess sensing capability to develop, co-develop, identify, and assess technological opportunities and reconfiguring capabilities (Fainshmidt et al., 2016) and seizing capabilities to appreciably mobilising the resources and to learn how to handle the technological operations.

Hence, with all these capabilities as envisaged by RBV and DCV, the firms are needed to supply rare, inimitable, accurate, and curated data to the system befitting with the dynamic market. The employees must have the abilities to operate the new technology (here AI integrated BA solution) successfully for which they need to have proper training. In failure, the system output will be poor and inappropriate training to the employees will render them incapable of handling the new system resulting in the adoption of an inappropriate AI integrated BA solution (Hindle & Vidgen, 2018). However, such lacunas may be removed if the management of the firms implements the needed requirements with governance (Winter & Davidson, 2019).

Thus, from the RBV theory and its extension to DCV, it is clear that for appropriate adoption of new technology in a firm, the firm should feed the system valuable, meaningful, rare, and useful data. This data is also known as quality data. For feeding quality data to the system, proper steps following a structured framework (governance) are to be followed by the system developers. Besides, the outputs from the system are to be understood by the employees of the firms. For this, the employees need to have proper training following a structured framework to enhance the level of understandability. Again, while sailing on with the operation, if there is any dislocation, the firm must possess a proper contingency plan to manage the situation. This concept is supported by the contingency theory (Pratono, 2016; Vroom & Jago, 1995). AI-BA opacity leads to an incorrect decision, which hampers the efficiency of operation of the firm, adversely impacting its performance and competitive advantage. To address the situation, alternative provisions must be there to meet the situation, which is the central theme of the contingency theory (Pratono, 2016).

Thus, with the inputs from resource-based view, dyanamic capability view and contingency theory, it may be inferred that operational inefficiency is prompted by the inappropriate decision and risks emerging from AI-BA opacity. Adoption of AI integrated BA solution becomes opaque if the poor quality of data is fed to the system consequent upon lack of governance.

3.2. Conceptual model and hypotheses development

Drawing on the big data analytics literature and inputs from RBV, DCV, and CT, we put forward our conceptual model (see Figure 1), which explicates how the adoption of an inappropriate AI integrated BA solution could adversely impact a business firm. The inputs of the literature and underpinning theories segment three clusters of factors to articulate our conceptual model. These are flawed technology strategy (1), risk environment due to inappropriate AI integrated BA solution, (2) and negative firm performance and competitive disadvantage (3) as follows.

3.2.1. Flawed technology strategy: An AI-BA opacity

As part of a flawed technology strategy, we argue that an AI-BA opacity consists of three components: lack of governance (LOG), poor data quality (PDQ), and inefficient training (INT). We shall now discuss these subdimensions separately to communicate how they reflect an AI-BA opacity.

3.3. Lack of governance

The idea behind AI governance is associated with a conception of having a pragmatic legal framework that would help the management of the firms to effectively adopt the AI system in the firms in a fair way to achieve the best result (Winter & Davidson, 2019). Good governance can bring success to a firm (Bock et al., 2020). Good governance is conceptualised as a structured process that a firm needs to follow for achieving its goal. Governance is a process followed by the firms with a scheduled framework to achieve measurable and intended outcomes (Winter & Davidson, 2019). In this study, governance basically refers governance of data scheduled to be fed to the AI integrated BA solution, governance on training for imparting proper training to the employees for best utilisation of the recommendations emerging from the outputs of the system and governance of the AI integrated BA solution in the firms. In the context of

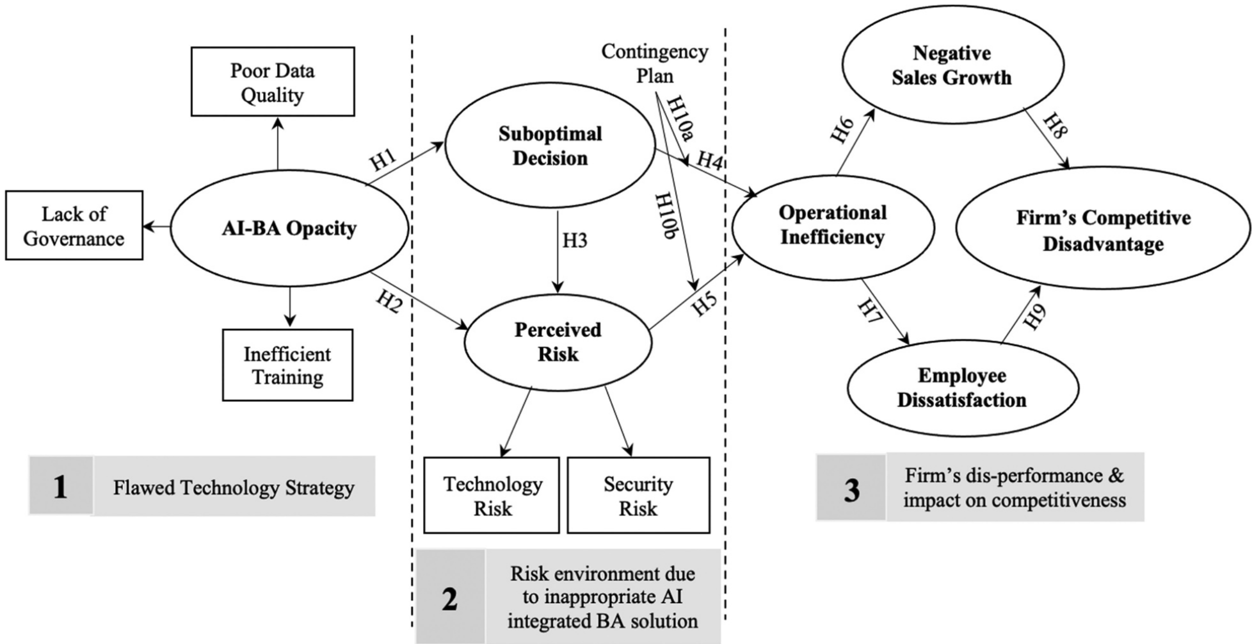

Figure 1. Conceptual model (Adapted from Kor & Mahoney, 2003; Teece et al., 1997; Vroom & Jago, 1995).

a firm, lack of AI governance might indulge in the acquisition of such data, which are not free from flaws. These data may not be valuable, usable, curated, rare, inimitable, or non-substitutable (Barney, 1991; Winter & Davidson, 2019).

AI governance concept is concerned with structuring an appropriate and consistent legal framework that would help the firm management effectively adopting any new technology. The aim of AI governance is to narrow the gap that might exist between accountabilities as well as ethics towards the adoption of the new technology. Moreover, different studies highlight that AI governance is the most critical component for effectively rolling out any AI-enabled solution (Winter & Davidson, 2019).

If there is better AI governance, it will help the firms effectively adopting AI solutions in a better way to derive the best results (Winter & Davidson, 2019). A firm would have to suffer a lot, if due to lack of governance, there is an inappropriate technology solution adopted by the firm (Lauterbach, 2019). As already stated, AI integrated BA solution would provide outputs with recommendations. However, the employees of the firms with their absorptive capacity need to understand and select such outputs, which would be useful for the benefits of the firms. For this, they are to be trained following a structured framework that would help to impart proper training to them. Thus, the training is to be imparted with good governance to enhance the employees' understanding to select such recommendations in the form of outputs emerging from AI integrated BA solution that would be useful to benefit the firms. In this perspective, it is essential that the employees of a firm should use the new system without any constraint. For this, the employees are needed to be imparted with appropriate training with good governance. Without having proper training, the employees of the firm would not be able to effectively use the new system, which may eventually cause enormous harm to the firm . Thus, an AI-BA opacity is reflected by a lack of governance.

3.4. Poor Data Quality

It is a well-known fact that data is considered to play a vital role towards meaningful as well as effective utilisation of any technology solution in a firm (Cosic et al., 2015). While acquiring data, it is important to note that the data so acquired should possess appropriate quality for effective and successful usage for any technology solution (Gunasekaran et al., 2017). Firms' management has a critical role in the acquisition of quality data (Sharma et al., 2014). It is relevant to note that accurate acquisition of resources would help the firms' management to take real-time decision. It would help the firm for the successful use of any technology solution (Bernhard et al., 2006). This concept has also been supplemented in DCV (Teece, 2014) as well as RBV theory, as previously discussed. These discussions highlight the necessity of the acquisition of quality data for achieving success in a firm. Data that are inconsistent, poorly defined, incorrect, and useless, as well as data that do not make much sense for the firms, are known as poor quality of data (Xu et al., 2020). If such poor quality of data is fed to the AI integrated BA solution, it might lead to harmful consequences for the firm. This apprehension is natural since if the input quality of data becomes poor, the output solution using that input data will lead to providing an inappropriate solution inimical for the firm (Harlow, 2018). If the firm uses AI solution, it is natural that governance of AI must be appropriate for ensuring the right kind of data acquisition for the AI-enabled solution of that firm (Marshall et al., 2015). Thus, an AI-BA opacity is also reflected by a lack of poor data quality.

3.5. Inefficient Training

For transferring, creating, and retaining knowledge necessary for the firms' development, a process is followed, which is called employee training (Maity, 2019). Studies have highlighted that improper training to the employees of a firm will result in an under usage of any new technology solution (Quinney & Richardson, 2014). Inefficient training in an AI environment occurs due to a poorly designed training programme, inefficient and ineffective trainers, incapability of the trainees (employees) to effectively execute the training in their workplace. Inefficient training leads to lower motivation of the trainees (employees) (Paschen et al., 2020). To use any AI-enabled solution in a firm, it is essential that the employees are trained properly. Inadequate training to the employees of a firm in the context of using AI-enabled solution causes a huge negative impact on the firm (Maity, 2019). In this perspective, AI governance, supposed to be augmented by the firm, plays a vital role in ensuring adequate and accurate training to the employees. By appropriate training, the employees will be able to use the technology in a more efficient and accurate manner (Quinney & Richardson, 2014). As such, an inefficient and ineffective training of employees is a critical component of an AI-BA opacity. Overall, we propose an AI-BA opacity as a higher-order construct, which consists of three reflective sub-dimensions: lack of governance, poor data quality, and inefficient training. In the following sections, we will put forward our hypotheses on the various effects of an AI-BA opacity.

3.5.1. Risk environment due to an AI-BA opacity

In order to assess the risk environment due to an **AI-BA opacity**, we argue that perceived risk (PRI) is reflected by technology risk (TER) and security risk (SER), which contribute to a suboptimal decision (SOD). We shall explain these factors separately for the formulation of hypotheses as follows:

3.6. Suboptimal Decision

If a firm adopts any business analytics solution with a focus on its objective, it is possible that the firm would take a real-time business decision (Appelbaum et al., 2017). It is known that big data may be considered as an important component of business analytics, and with a thorough analysis of big data, it is possible for the firm management to arrive at a congenial business decision helpful for the firm (Chae et al., 2014). Accurate business analytics helps firm management to take an appropriate business decision (Ramanathan et al., 2017). If the poor quality of data is fed into the AI integrated BA solution (Tallon 2013), or if the AI integrated BA system itself has design-flaw (Ghasemaghaei & Turel, 2021), or if the AI algorithmic design is biased, the outputs of the whole system will be inappropriate and biased (Davenport 2020; Wixom et al., 2020). An AI integrated BA solution based on incorrect or inadequate training data might lead to a suboptimal decision (Kaplan & Haenlein, 2019). These inputs help us to formulate the following hypothesis:

H1: AI-BA opacity *will lead to a suboptimal decision.*

3.7. Perceived Risk: Technology Risk and Security Risk

The concept of technology risk is associated with technical failures that adversely influence the growth of the business of a firm (Khaksar et al., 2019). It is natural that AI technology needs to be applied in a firm in a congenial way so that the firm would face a minimum amount of risk. It has already been mentioned that the part played by the business analytics solution helps the firm to take the right decision at the appropriate time. If with business analytics AI is integrated, the decision is made automatically. But on the contrary, inappropriate development of AI integrated business analytics solution will lead to enhance overall risk to the firm (Masakowski, 2020; Yeoh, 2019). The nature of technology risk is perceived to have undergone continuous changes owing to the entry of emerging technologies like Blockchain, AI and so on (Marks, 2008). But if these modern technologies are not applied in a right way, it would invite untoward risks, and it would cause an increased risk to the entire firm affecting its efficiency adversely. According to the risk management survey conducted by KPMG (2017), it has been confirmed that in this first-paced disruptive world, there is a need of adopting appropriate technology risk management mechanisms. It has also been observed in the survey that many firms operated digitally do not attach any importance to this technology risk as an important value centre, but they stick to comply with traditional approaches to these technology risk issues, and as a result, they do not have control over technological assets that impairs innovation. Thus, the overall perceived risk (PRI) perception of a firm is reflected by technology risk (TER) relating to AI integrated business analytics solution.

It is known that information security risk is associated with the threats and vulnerabilities related to the process and operation of the information systems of the firm (Kuo et al., 2010). For mitigating the risk, there is a need for continuous monitoring and maintenance of preventive and correctional security control for protecting the information-centric assets from being damaged (Liebermann & Stashevsky, 2002). Many other types of risks are associated with the information security risk, which is otherwise known as data-security risk (Vermeulen & Von Solms, 2002). Obviously, security risk brings in security concerns for a firm. This security concern is enhanced many folds as a culmination of AI-BA opacity (Nam, Lee & Lee, 2019), which eventually enhances the perceived risk of the firm. However, if an appropriate plan is devised in this context, it can address the security-related challenges that may occur as a result of the adoption of an opaque AI-BA solution (Klatt et al., 2011; Yeoh, 2019). However, the absence of such type of backup plan might enhance the security-related concern of the firm, which will also enhance its overall perceived risk (Post & Kagan, 2006). Thus, the overall perceived risk (PRI) perception of a firm is reflected by security risk (SER) concerning to AI integrated business analytics solution.

Perceived risk is considered as a mixed effect of seriousness and uncertainty of the outcomes concerning the issues of safety and performance associated with societal, business, and psychological uncertainties (Egea & González, 2011). It is a fact that firms will incur huge loss owing to the adoption of inappropriate AI integrated BA solution, and it invites risks (Marks, 2008). This risk-related issue is considered one of the biggest challenges a firm would face. Without proper AI governance, any AI-enabled solution will pose a threat to the firm (Lauterbach, 2019; Winter & Davidson, 2019). There are many firms that do not have enough trained employees to handle such threat that might take place consequence upon adoption of inappropriate AI integrated BA solution (Nam, Lee & Lee, 2019). The employees of the firm may perceive that it is very difficult to learn to adopt AI integrated solution, and this perception invites risks (Stern et al., 1977). In terms of these inputs, the following hypothesis is developed:

H2: AI-BA opacity will result in increased perceived risk.

Since AI integrated BA goes beyond traditional analytics technologies by approximating human cognitive decisions to take diagnostic, predictive or prescriptive actions, it presents significant risks to a firm (Davenport et al., 2020). For example, the Anderson Cancer Center in the US has suffered a substantial failure in developing an AI-enabled cancer diagnosis system after investing 62 million USD in four years (Jaklevic, 2017). Similarly, the AI-based "Robo-debt Scheme" by the Australian Taxation Office (ATO) has unlawfully pursued hundreds of thousands of welfare clients for the debt they did not owe (Hunter, 2020). Due to this inappropriate AI integrated analytics, ATO would repay in full 470,000 victims who received false debt notices, with an estimated A $721 million to be refunded (ABC News, 2020). An inappropriate system might lead to suboptimal business decision and might end up in providing wrong strategic directions on how to manage and leverage it to achieve success (DeLone & McLean, 2003). Thus, it has been already argued that if a firm adopts an opaque AI-BA solution, it will lead the firm to adopt an inappropriate business decision with potential technology and security risk. This suboptimal business decision will cause harms to the firm. This would also cause multifarious risks to the firms. The firm might survive if it has some appropriate and effective mitigation plan in place (Antunes et al., 2014; Ramanathan et al., 2017). With all the above discussion, the following hypothesis is proposed:

H3: Suboptimal business decision has a significant impact on perceived risk.

We have already argued that the adoption of an opaque AI-BA solution in a firm will lead the firm to take a suboptimal business decision, and this inappropriate business decision will invite multifarious risks to the firm. We have already detailed the reasons for this. Now, such suboptimal business decision will retard the firm's progress and eventually, it would affect the efficiency level of the firm adversely. In other words, it will enhance the firm's operational inefficiency (Brauner et al., 2019; Ilyina et al., 2019). For this, a congenial mitigation plan to be in place may help the firm to come out from these constraints as supplemented by the Contingency Theory (Pratono, 2016; Vroom & Jago, 1995). A suboptimal business decision often misleads the firm to take appropriate steps. It results in inefficiency. Inefficiency in the operation of the firm costs more money. It incurs wastage of time affecting and diminishing quality of work. It also enhances the risk factor preventing the firm from sticking to its targeted strategic goal. In view of the above discussions, the following hypothesis has been formulated:

H4: Suboptimal business decision will lead to the firm's operational inefficiency.

Due to the adoption of an opaque AI-BA solution, the perceived risks of the firm may be enhanced. If there is no proper mitigation plan in place, it is apprehended that the firm's operational efficiency will be adversely affected (Jayashankar et al., 2018). For example, Weissman (2018) reported that the efficiency of Amazon's AI-based recruitment system has been questioned and abandoned in recent years due to gender bias and equity risks. Similarly, in providing customised healthcare, Optum's AI-based health analytics platform has suffered significant operational inefficiency due to incorrect training data, inappropriate medical algorithm and relevant technology risks (Blier, 2019). Hence, an increase of perceived risks without a contingency plan, as supported by the contingency theory (Pratono, 2016; Vroom & Jago, 1995), might degrade the operational efficiency of the firm. From these inputs, the following hypothesis is developed:

H5: Perceived risk will result in the increase of a firm's operational inefficiency.

3.7.1. Negative firm performance and firm's competitive disadvantage

Four constructs which are operational inefficiency (OPI), negative sales growth (NSG), employee's dissatisfaction (EDS) and a firm's competitive disadvantage (FCD) have been grouped in this segment. We will now explain these factors separately to formulate the hypotheses:

3.8. Operational Inefficiency, Negative Sales Growth, and Employees Dissatisfaction

It is known from the other studies that there exists a close relationship between the adoption of new technology and the operational efficiency of a firm in the perspective of competitive advantage (Cosic et al., 2015; Elbashir et al., 2008). A firm can maintain appropriate operational efficiency if proper investments are made for adopting business analytics solution in that firm (Appelbaum et al., 2017). Tangible as well as intangible efficiencies of a firm can be achieved by the adoption of appropriate BA solution (Appelbaum et al., 2017; Sun & Pang, 2017). Due to the adoption of any inappropriate technological solution, it is seen that the firm management could take inappropriate business decision. This suboptimal business decision may impact the operational efficiency of the firm (Croom et al., 2018). These arguments lead us to formulate the following hypothesis:

H6: Higher firm's operational inefficiency will result in superior negative sales growth.

In a study, it has been observed that the use of optimum business analytics solution makes the firm an evidence-based problem-solving firm. It supplements the operational efficiency of the firm (Holsapple et al., 2014). Adoption of appropriate BA solution in a firm improves the operational transparency of that firm, which leads to conceptualise that if there exists any risk, the efficiency of operation is adversely affected (Papadopoulos & Karagiannis, 2009). A suboptimal business decision may impact the operational efficiency of the firm (Croom et al., 2018). It appears that operational inefficiency affects the name and fame of the firm, which impacts the satisfaction level of the employees in the firm (Dustin & Belasen, 2013). The firm's market share is adversely affected in such a situation (Amissah et al., 2016; Croom et al., 2018). With the above discussion, the following hypothesis is proposed:

H7: Higher firm's operational inefficiency will lead to higher employee' dissatisfaction.

3.9. Firm's Competitive Disadvantage

Competitiveness is considered as the ability of a firm for producing goods or services, which are supposed to successfully match the needs of the markets. It appears that firms are involved in competition with one another concerning the extent of their share in the domestic or international market (Karabag et al., 2014). The competitiveness is assessed by the study of how the firm is able to upgrade and improve quickly by enhancing its market value compared to the other players (Cerrato & Depperu, 2011). It can be said that if the sales growth is declined, the firm may lose its market share domestically and globally (Sun & Pang, 2017). When the operational efficiency of a firm decreases, it badly affects the sales function of a firm. Consequently, the firm cannot optimise its competitive advantage. Due to the unpredictable nature of AI integrated BA, we argue that a strategic fit or alignment is critical among various resources (e.g., talent, data, technology, and management) to enhance firm performance (e.g., sales) and competitive advantage (Barney, 1991; Pfeffer, 1994; Peteraf, 1993). According to RBV, firms need to effectively deploy their AI-integrated BA resources to increase their outcomes (Wamba et al., 2017). Past IS literature has reported the positive relationship between IT resources and firm performance to achieve competitive advantage (e.g., Bhatt & Grover, 2005; Kim et al., 2012; Pavlou & El Sawy, 2006; Tippins & Sohi, 2003); however, there is little knowledge on the impact of an AI-BA opacity. Thus, we put forward the following hypothesis:

H8: Higher negative sales growth of a firm will lead to a firm's competitive disadvantage.

The success of a firm depends on many factors. Among these factors, the sincerity and working abilities of the employees of a firm count much because their working abilities pull the firm towards success. Hence, the firm management is always needed to boost up the morale of the employees for extracting the best potentials from them (Karabag et al., 2014). Through the service-profit-chain lens, Heskett et al. (1994) illuminate that a firm should focus on the satisfaction of its employees first to enhance its financial performance. Reflecting the tenets of the service-profit chain, Google, one of the most innovative corporations on earth and a leader in AI, states that "we want our employees and future employees to love it here, because that's what's going to make us successful" (Crowley, 2013). As such, a Google spokesman states that the company aims "to create the happiest, most productive workplace in the world" (Stewart, 2013, p. B1). Thus, employee satisfaction is identified as a major driver of firm productivity (Hogreve et al., 2017). It is observed that if for any reason employees' morale is declined, it eventually affects the competitive edge of the firm (Cerrato & Depperu, 2011). These discussions help us to formulate the following hypothesis:

H9: Higher employee's dissatisfaction will result in a firm's competitive disadvantage.

3.9.1. Moderating effect of contingency plan

In this study, we have used moderating effects of "Contingency Plan" on the two linkages, i.e., H10a and H10b. A contingency plan is considered a risk management plan to address any unforeseen outcome. In terms of contingency theory (Pratono, 2016; Vroom & Jago, 1995), it is expected that the firms will devise a backup plan, which will help the firm to overcome any hindrance caused by the adoption of an opaque AI-BA solution (Donaldson, 2001). Managers need to examine the internal and external environments to structure the contingency plan embedded with different options (Jordan, 1999; Sousa & Voss, 2008). For many reasons, including the adoption of inappropriate technology, a firm sometimes takes a suboptimal business decision. This wrongful business decision affects the operational inefficiency of the firm. If the firm has an effective business continuity plan in place, it can help to moderate the impacts of inappropriate business decisions on the operational efficiency level of the firm (Simpkins, 2009). Hence, it is hypothesised as follows:

H10a: The contingency plan has a considerable moderating effect on the SOD → OPI (H4) linkage.

Several studies highlighted that the firms could work in an efficient way with the proper business continuity plan if its regular way of operation is degraded due to some system failure (Simpkins, 2009). In that case, the firm invites some unwanted risks. These risks affect the operational efficiency of the firm. However, if the firm has a strong contingency plan to overcome this situation (Hall et al., 2012), the firm can survive. In view of the above discussions, we formulate the following hypothesis:

H10b: The contingency plan has a considerable moderating effect on the PRI → OPI (H5) linkage.

4. Research Methodology

4.1. Research Instrument

With the assistance of extant literature, inputs from the theoretical background, and from the knowledge of the existing scale, items for measuring the constructs have been prepared to confirm content validity. However, a series of rectification process with a step-by-step approach (Carpenter, 2018), 33 items have been prepared so that they become appropriate in the context of this study. The details of the instruments with sources are shown in a tabular form in Appendix 1. After preparing the 33 items, six experts having expertise in the domain of the study have been consulted to rectify the imperfections of readabilities and ensuring validity. With their valued opinion, some minor corrections have been made in some of the items for capturing competitive disadvantage. We have also conducted a pretest for validation of these 33 items, and the items have been duly rectified with the inputs available from the pretest. In this way, we could finally prepare 33 measurement instruments. Those items were provided to the usable respondents for getting their responses and were quantified through a 5-point Likert scale.

4.2. Data Collection Strategy

For targeting the potential respondents to collect usable responses, one of the researchers used his industrial links of key officials at associations of business organisations in India, including the Federation of Indian Chambers of Commerce & Industry (FICCI), Confederation of Indian Industry (CII), and National Association of Software and Service Companies (NASSCOM). For collecting data swiftly in the specific format with minimal cost, we created an online questionnaire using Google Docs, and the link of the questionnaire was shared with the known key officials in these associations of business organisations. Through their widespread links into various operating into financial, information technology (IT), healthcare, telecommunication, retail, and hospitality sectors, it was possible to send a questionnaire to some selected but all different sizes of organisations and managers with their different areas of expertise and experience.

Since the business decisions are mostly taken by the management of the firms, it was planned to focus the efforts to collect data only from the managerial ranked individuals. To achieve better response rate, several attempts have been taken. The questionnaire was prepared in such a way that the respondents could clearly understand the questions. Besides, the questions were prepared in such a fashion as we could realise the notion of the respondents regarding their understanding of how inappropriate adoption of AI integrated BA could fetch a downfall towards operational efficiency of a firm (Harzing et al., 2012; Mellahi & Harris, 2016). Besides, with the response sheet, it was informed how to respond appropriately and further, it was also assured to them that their confidentiality and anonymity would be strictly preserved (Chidlow et al., 2015).

In this way, the questionnaire was sent to 1,104 individuals holding managerial positions in different service industries, as mentioned above. All these 1,104 managers were requested to provide their responses to the questionnaire within four weeks of turnaround time between February and March 2020. Within the scheduled time, we received 403 responses with a response rate of 36.5%. The responses so received were further evaluated, and it was found that out of 403 responses, 48 were not complete. As a result, we removed these responses from the final usable data and started working with 355 valid responses. Detailed characteristics of the sample (*n* = 355) are provided in Table 1.

Table 1. Characteristics of the sample.

Characteristics	Category	Number	Percentage (%)
Management hierarchy	Senior Manager	85	23.9
	Mid-level Manager	118	33.3
	Operational Manager	152	42.8
Organizational characteristics (Based on revenue)	Large Organization (Revenue of > USD1 billion per year)	155	43.7
	Mid-level Organization (Revenue of >USD100 million to 1 billion per year)	112	31.6
	Small Organisation (Revenue of < USD100 million per year)	88	24.7
Industry type (Services)	Financial Service	78	22
	IT Service	89	25
	Healthcare Service	36	10
	Telecommunication Service	52	15
	Retail Sector	50	14
	Hospitality Sector	50	14

5. Data Analysis and Results

The study applied the partial least squares (PLS) structural equation modelling (SEM) to estimate the research model as it provides robust results for a complex, hierarchical model (Becker et al., 2012; Wetzels et al., 2009). Using the guidelines of Becker et al.'s (2012) repeated indicator approach, we estimated two higher-order constructs: an inappropriate AI integrated BA and perceived risk. As such, we repeatedly used the items of the first-order constructs of to estimate these two higher-order constructs. To analyse the results, PLS-SEM approach has been taken (Akter et al., 2017; Hair et al., 2016) using Smart PLS 3.2.3 software (Ringle et al., 2015) with a non-parametric bootstrapping of 5,000 replications to estimate path coefficients and test the hypotheses.

Table 2. Measurement properties.

Construct/ Items	Mean	SD	LF	*t*-Values	AVE	CR	Alpha (α)
PDQ					0.85	0.88	0.92
PDQ1	3.8	1.1	0.90	21.11			
PDQ2	4.6	1.7	0.95	22.27			
PDQ3	3.9	1.6	0.92	38.11			
LOG					0.83	0.87	0.90
LOG1	4.1	1.9	0.87	34.07			
LOG2	4.5	1.2	0.91	26.15			
LOG3	3.7	1.1	0.95	25.67			
INT					0.89	0.93	0.96
INT1	3.2	1.6	0.97	29.14			
INT2	4.8	1.4	0.85	26.22			
INT3	3.2	1.7	0.91	22.54			
SOD					0.87	0.91	0.94
SOD1	3.1	1.2	0.90	24.11			
SOD2	4.2	1.4	0.95	23.62			
SOD3	3.7	1.5	0.85	26.71			
TER					0.86	0.90	0.93
TER1	3.6	1.6	0.94	25.24			
TER2	3.1	1.3	0.90	26.12			
TER3	3.9	1.4	0.95	22.18			
SER					0.88	0.92	0.94
SER1	4.2	1.2	0.91	26.19			
SER2	3.4	1.1	0.96	38.17			
SER3	3.7	1.7	0.95	41.12			
OPI					0.86	0.88	0.93
OPI1	3.2	1.3	0.88	48.17			
OPI2	3.6	1.2	0.97	33.18			
OPI3	3.9	1.4	0.90	39.07			
NSG					0.84	0.89	0.94
NSG1	4.1	1.4	0.96	32.41			
NSG2	3.5	1.3	0.94	37.22			
NSG3	4.8	1.7	0.91	38.11			
EDS					0.80	0.84	0.88
EDS1	4.2	1.6	0.94	36.11			
EDS2	3.6	1.9	0.85	32.17			
EDS3	4.6	1.8	0.90	21.12			
FCD					0.86	0.92	0.97
FCD1	4.2	1.7	0.95	26.61			
FCD2	3.4	1.6	0.86	37.17			
FCD3	3.1	1.4	0.97	38.89			
COP					0.81	0.85	0.90
COP1	4.2	1.7	0.95	26.59			
COP2	3.8	1.4	0.85	31.37			
COP3	3.4	1.1	0.90	39.09			

5.1. Data Analysis

Table 2 presents the measurement properties of all the first-order constructs. In terms of the measurement model, it is to note that we have estimated the convergent validity of all the items of the constructs. For this, the loading factor (LF) for each item has been estimated for all the first-order constructs (see Table 2). It was observed that all the item loadings are more than 0.70 (Chin, 2010). The estimates of LFs were found between 0.85 and 0.97. For measuring reliabilities and validities of the constructs, we estimated composite reliability (CR) and average variance extracted (AVE) of all the constructs. All the estimates of CRs and AVEs are found to be greater than 0.80 and 0.50, respectively (Hair et al., 2017). To estimate the consistency of the constructs, we have measured Cronbach's alpha (α) of each construct. All the results are shown in Table 2.

The study has developed the AI integrated BA opacity (ABO) construct as a second-order, reflective construct, which is explained by its three subdimensions. These are poor data quality (PDQ), lack of governance (LOG), and insufficient training (INT). Similarly, perceived risk (PRI) is a second-order, reflective construct, explained by two subdimensions: technology risk (TER) and security risk (SER). The number of items of PDQ, LOG, and INT is three, each consisting of the total items of ABO as (3 + 3 + 3) = 9. Similarly, the number of items of TER and SER is three, each consisting of the total items of PRI as (3 + 3) = 6. All the loadings, CR, AVE, and other parameters of the higher-order dimensions have been shown in Table 3.

Significance: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table 3. Second-order relationship.

Construct	Loading	CR	AVE	*p*-Value	Relationship	β-Value	*t*-Value
I-BA Opacity (ABO)	0.90	0.89	0.85	***	ABO→PDQ	0.87	29.49
	0.95						
	0.92						
	0.87	0.88	0.83	***	ABO→LOG	0.81	24.72
	0.91						
	0.95						
	0.97	0.92	0.89	**	ABO→INT	0.77	30.01
	0.95						
	0.91						
Perceived Risk (PRI)	0.94	0.84	0.81	***	PRI→TER	0.79	17.41
	0.90						
	0.85						
	0.91	0.92	0.88	**	PRI→SER	0.83	36.26
	0.96						
	0.95						

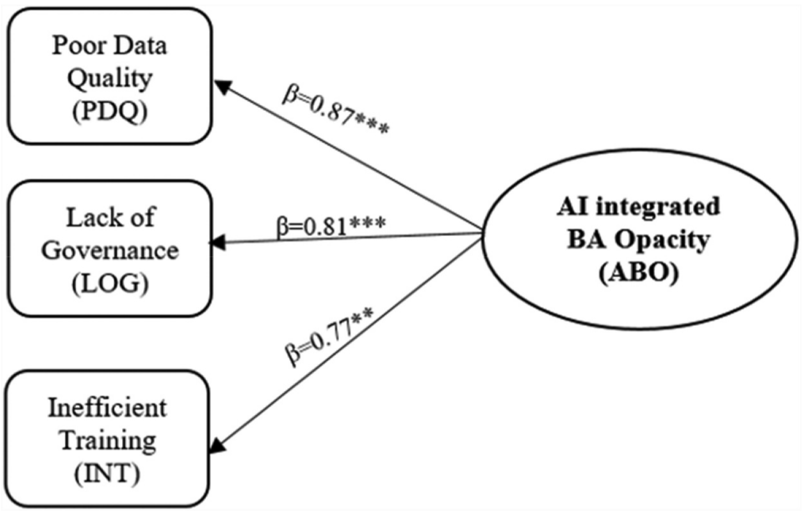

Figure 2. Construct (ABO) and its subdimensions.

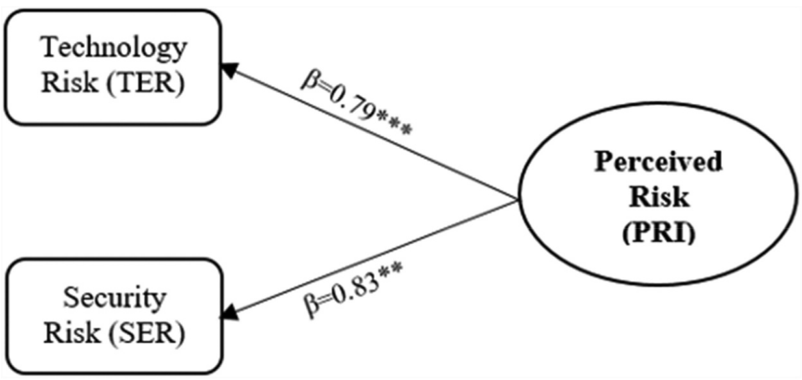

Figure 3. Construct (PRI) and its subdimensions.

Table 4. Discriminant validity test.

Construct	EDS	FCD	SOD	INT	LOG	NSG	OPI	PDQ	SER	TER	AVE
EDS	0.89										0.80
FCD	0.22	0.93									0.86
SOD	0.32	0.19	0.93								0.87
INT	0.21	0.27	0.29	0.94							0.89
LOG	0.29	0.26	0.26	0.24	0.91						0.83
NSG	0.24	0.31	0.22	0.27	0.29	0.92					0.84
OPI	0.37	0.41	0.33	0.29	0.33	0.27	0.93				0.86
PDQ	0.31	0.39	0.19	0.31	0.42	0.31	0.17	0.92			0.85
SER	0.24	0.37	0.29	0.37	0.29	0.24	0.19	0.28	0.94		0.88
TER	0.23	0.18	0.24	0.36	0.28	0.32	0.26	0.32	0.27	0.90	0.81

All the estimates in connection with the dimensions are found to be within the specified range. We have also estimated the path coefficients between ABO and its three subdimensions as well as PRI and its two subdimensions, which have been proven as a significant component at $p < 0.001$. These are shown in Figures 2 and Figures 3.

Table 5. Structural model.

Linkages	Hypotheses	R^2/β-values	p-Values	Remarks
Effects on SOD		$R^2 = 0.26$		
By ABO	H1	0.21	<0.01(**)	Supported
Effects on PRI		$R^2 = 0.33$		
By ABO	H2	0.26	<0.05(*)	Supported
By SOD	H3	0.22	<0.001 (***)	Supported
Effects on OPI		$R^2 = 0.39$		
By SOD	H4	0.27	<0.001 (***)	Supported
By PRI	H5	0.29	<0.05(*)	Supported
Effects on NSG		$R^2 = 0.43$		
By OPI	H6	0.24	<0.01(**)	Supported
Effects on EDS		$R^2 = 0.41$		
By OPI	H7	0.33	<0.001 (***)	Supported
Effects on FCD		$R^2 = 0.67$		
By NSG	H8	0.43	<0.001 (***)	Supported
By EDS	H9	0.45	<0.001 (***)	Supported
(SOD→OPI) × COP	H10a	0.17	<0.05(*)	Supported
(PRI→OPI) × COP	H10b	0.23	<0.01(**)	Supported

5.2. Discriminant Validity Test

We have assessed the discriminant validity of all the first-order constructs. Applying the Fornell and Larcker criterion (Fornell & Larcker, 1981), the findings show that the square roots of all the AVEs are greater than the corresponding bifactor correlation coefficients. It confirms the discriminant validity of the constructs. The results are presented in Table 4.

5.3. Structural Model

PLS-SEM helps to provide a clear idea about how the latent variables are related to each other. It also provides an impression of the model is in order or not. For conducting PLS-SEM, some fit indices and root-mean-square error (RMSE) are required to be assessed. These help to confirm whether data can be correctly represented by the structure. The ratio of chi-square and degree of freedom, Comparative Fit Index (CFI), Normal Fit Index (NFI), Tucker–Lewis Index (TLI), and RMSE have been estimated. These estimated values are 2.013, 0.95, 0.97, 0.98, and 0.03, respectively. All the estimated values are within the permissible range. Hence, the model is in order, and the data could represent the structure correctly. Therefore, we move on to the structural model to test the formulated hypotheses. The entire results

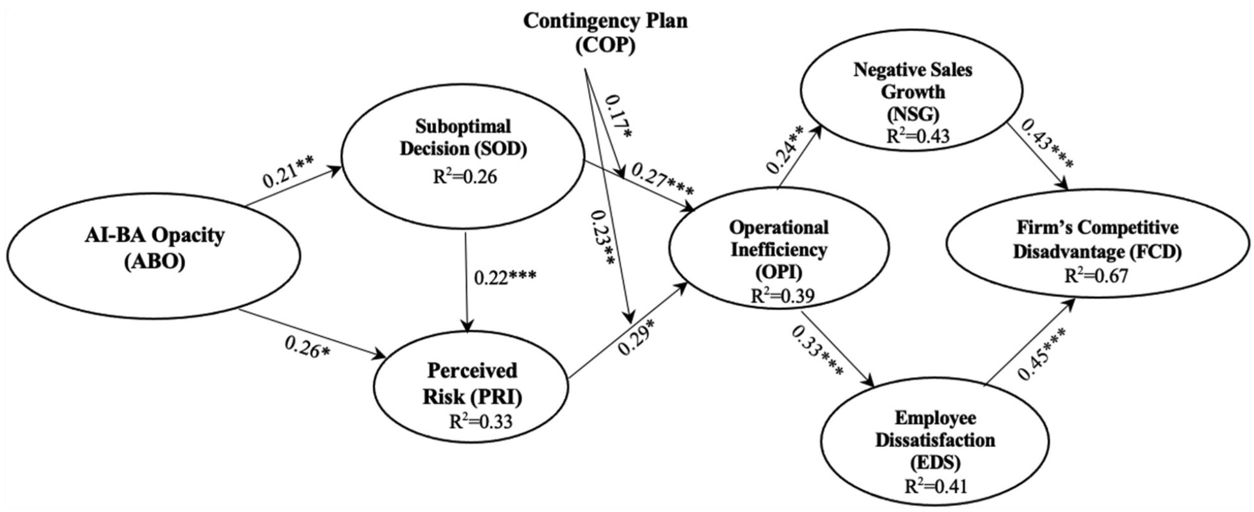

Figure 4. Validated research model.

with coefficients of determinant, path coefficients, and p-values are presented in Table 5.

The validated research model is shown in Figure 4.

This study has formulated 11 hypotheses. Out of these 11 hypotheses, 2 hypotheses are related to the moderating effects of COP on the two linkages H4 (SOD→OPI) and H5 (PRI→OPI). The moderator's impacts on H4 and H5 are designated as H10a and H10b, respectively. This study has shown that ABO can be conceptualised by its three reflective dimensions PDQ, LOG, and INT. Also, PRI can be interpreted by two reflective dimensions: TER and SER. The adoption of inappropriate AI integrated BA solution is caused by the poor quality of input data, lack of governance from the management side, and inefficient training imparted to the employees. These shortcomings eventually invite inappropriate AI application in the context of big data leading to a faulty analysis by BA. This study highlights that ABO could impact SOD (H1) and PRI (H2) significantly since the concerned path coefficients are 0.21 and 0.26 with levels of significance as $p < 0.01$(**) and $p < 0.05$(*).

Again, SOD is found to have impacted PRI (H3) and OPI (H4) significantly as the concerned path coefficients are 0.22 and 0.27, respectively, with levels of significance as $p < 0.001$(***) in each case. The results show that PRI impacts OPI (H5) significantly since the concerned path coefficient is 0.29 with the level of significance as $p < 0.05$(*). The results also highlight that OPI significantly impacts NGS and EDS (H6 and H7) since the path coefficients are 0.24 and 0.33, respectively, with levels of significance as $p < 0.01$ (**) and $p < 0.001$(***). It appears from the results that NSG and EDS simultaneously impact FCD (H8 and H9) significantly since the concerned path coefficients are 0.43 and 0.45, with each having level of significance $p < 0.001$(***). The moderator COP also impacts H4 and H5 significantly since the concerned path coefficients for the impacts (H10a and H10b) are 0.17 and 0.23, respectively, with significance levels $p < 0.05$(*) and $p < 0.01$(**), respectively.

In terms of R^2 values, it appears that ABO, being explained by the three reflective dimensions PDQ, LOG, and INT, could explain SOD to the extent of 26%, PRI could be simultaneously explained by ABO and SOD to the tune of 39%. Again, SOD and PRI could explain OPI to the extent of 33%. This study has also shown that OPI could explain NSG as well as EDS to the tune of 43% and 41%, respectively. All these explained variances are high as well as significant, confirming the effectiveness of the model. Finally, NSG and EDS could explain FCD to the extent of 67%, which is the predictive power of the model.

We have also estimated f^2 values for assessing if there is any effective contribution of exogeneous latent variable (i.e., ABO) on the corresponding endogenous variables (i.e., SOD, PRI, OPI, NSG, EDS and FCD). According to Cohen (1988), f^2 values indicate weak (0.020–0.150), medium (0.50–0.350), and large (>0.350) effect sizes. Our findings show that the effect size of ABO on SOD is 0.442; ABO on PRI is 0.481; SOD on PRI is 0.271; SOD on OPI is 0.05; PRI on OPI is 0.101; OPI on NSG is 0.211; OPI on EDS is 0.262; NSG on FCD is 0.389; and EDS on FCD is 0.421. The results are presented in Table 6.

5.4. Moderation Analysis

For estimating the effects of the moderator, contingency plan (COP), on the two linkages covered by H4 and H5, a multi-group analysis (MGA) has been adopted. This has been done with the help of Smart PLS and it has utilised bias-correlated accelerated bootstrapping with consideration of 5,000 resamples for ascertaining the p-value differences on the effects of the moderator, COP on the two linkages covered by H4 and H5 in the two selected categories of COP, which are strong contingency plan and weak contingency plan. The effects of the moderator on the two linkages are perceived to be significant if the differences in probability values for the two categories of the moderator become less than 0.05 or greater than 0.95 (5% probability value difference) (Hair et al., 2016). The moderator COP acts on the linkage SOD→OPI, and this moderating hypothesis is marked as H10a, whereas COP acts as a moderator on the linkage PRI→OPI, and this moderating hypothesis is marked as H10b. Both these hypotheses H10a and H10b are found significant as they each possesses p-value differences for strong COP and weak COP to the extent of 0.04 and 0.01 respectively being each less than 0.05. As such, the effects of the moderator on the two linkages are significant, which are shown in Table 7.

Table 7. Moderator verification (MGA).

Linkages	Moderator	Hypotheses	p-Value difference	Remarks
(SOD→OPI) × COP	COP	H10a	0.04	Significant
(PRI→OPI) × COP	COP	H10b	0.01	Significant

Table 6. Effect sizes.

	SOD	PRI	OPI	NSG	EDS	FCD
ABO	0.442 (L)	0.481 (L)				
SOD		0.271 (M)	0.05 (W)			
PRI			0.101(W)			
OPI				0.211(M)	0.262 (M)	
NSG						0.389 (L)
EDS						0.421 (L)

L: large; M: Medium; W: Weak.

5.5. Common Method Bias (CMB)

Since we have undertaken the study with the help of self-reported data, it is necessary to examine whether the data so collected is not biased. Practically, to minimise the risks of having biasness in the collected data, we assured the usable respondents in the survey that their confidentiality, as well as anonymity, will be strictly preserved so that they can provide their responses in an unbiased manner. We have conducted Harman's single-factor test as a post-doc analysis, which highlighted that the first factor could emerge only for 37.9% of the variance. It is safely less than the highest cut-off value 50% (Podsakoff et al., 2003). To address some of the limitations of Podsakoff et al. (2003), we have conducted a non-response bias analysis (Stanko et al., 2012) and a marker variable analysis (Lindell & Whitney, 2001), and the results did not provide any evidence of bias.

5.6. Robustness analysis of the model using PLSpredict

PLSpredict analysis helps in assessing the predictive robustness of PLS-SEM outcomes (Shmueli et al., 2019). This analysis process divides the samples into segments to assess the predictive power of the overall model on the outcome construct, which is the firm's competitive disadvantage (FCD) in our case. Following the guidelines of Shmueli et al. (2019), we ran the PLSpredict by sudividing the sample into 10 with 10 repetitions. Thus, the predictive robustness of the model is validated through PLSpredict (k = 10) using a training sample (n = 320) and a holdout sample (n = 35). The results contain assessments of root-mean-square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Q^2 for a few analysis types, that is, PLS-SEM, a linear regression model (LM), and PLS-LM. The results show that MAE values lie between 0.891 for FCD3 and 0.942 for FCD1 concerning PLS-SEM, from 0.881 to 0.944 for FCD3 and FCD1 respectively concerning LM, and between −0.005 for FCD3 and 0.002 for FCD1 concerning PLS-LM. It provides a glimpse of the robustness of the proposed model by assessing the out-of-sample predictive relevance of the FCD. We have also measured RMSE and Q^2 for PLS-SEM, LM, and PLS-LM. However, in the estimation of average model performance MAE is considered advantageous compared to the assessment of RMSE (Willmott & Matsuura, 2005). Again, to what extent the prediction is accurate can be measured by estimating MAPE (Tofallis, 2015). The results highlight that for PLS-SEM, MAPE lies between 20.949 and 22.841; for LM, it lies between 21.104 and 22.912, and for PLS-LM, it is between −0.100 and 0.029. All these parameters have been estimated for the indicators of FCD, which is our ultimate dependent variable. Overall, the findings show that the model possesses better predictive power as a culmination of eventual impacts of negative sales growth (NSG) and employee's dissatisfaction (EDS) on firm's competitive disadvantages (FCD) (Shmueli et al., 2019).

6. Discussion

The findings of the study show that due to lack of governance, there is a chance of supply of poor quality of data in the AI integrated business analytics system. This lack of governance also results in inefficient training imparted to the employees of the firm. Consequently, there is a possibility of the adoption of an opaque AI-BA solution in the firm. This also results in bringing risks to the firms, and these risks influence the management of the firms to lead to take inappropriate business decision negatively impacting the operational efficiency of the firm. All these eventually would adversely affect the competitive advantage of the firm.

The results highlight that with good governance, data quality is needed to be improved and the employees of the firms should be imparted effective training, so that appropriate AI integrated business analytics solution is ensured. In this perspective, PDQ, LOG, and INT have been considered as the three subdimensions for ABO (Sharma et al., 2014; Marshall et al., 2015; Nam et al., 2019; Xu et al., 2020). This study has also considered technology and security risk as two reflective subdimensions of perceived risk. It has been conceptually supported by a study by Post and Kagan (2006) where it has been observed that risk concerning security issue could affect the risk factors of the firms. This study has revealed that ABO will influence and mislead the firm management, and the firm management would ultimately adopt inappropriate business decision multiplying firms' risk factors. This will culminate operational inefficiency of the firm. Thus, our findings support H1–H5. The conceptual relationships

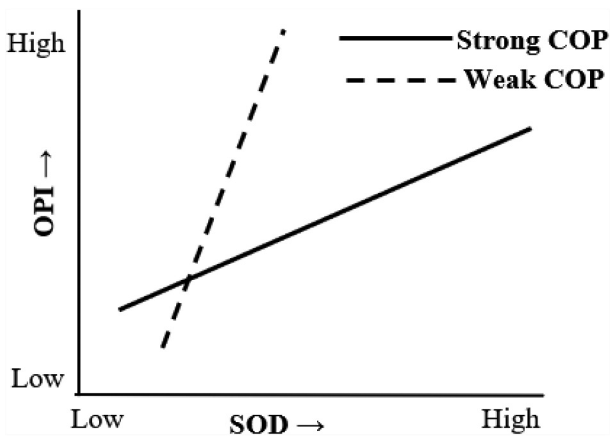

Figure 5. Effects of COP on H4.

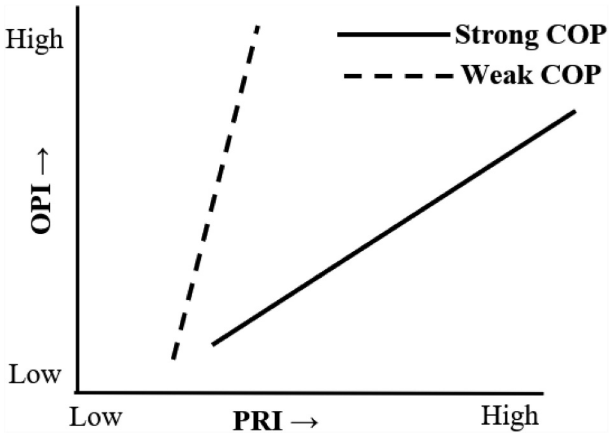

Figure 6. Effects of COP on H5.

based on the hypotheses have received support from several earlier studies (Croom et al., 2018; Holsapple et al., 2014; Jayashankar et al., 2018).

The results also highlight that OPI will impact the satisfaction level of the employees of the firms adversely, which will be inimical towards the competitiveness of the firms. Moreover, OPI will adversely affect the sales growth for which the firms will not be able to compete with their other counterparts. This is in conformity with the findings of H6-H9. Our findings based on these conceptual relationships and the validated hypotheses are aligned with the extant literature (Amissah et al., 2016; Bolander et al., 2017; Claro & Ramos, 2018). The moderator COP is found to have significantly impacted the two linkages H4 and H5. This idea has been supplemented both by the concept of contingency theory as well as other studies (Donaldson, 2001; Sousa & Voss, 2008). Figure 5 shows the effects of strong COP and weak COP on H4 (SOD→OPI). In this graph, SOD has been plotted in the horizontal axis, whereas OPI has been plotted in the vertical axis. SOD is considered here as an independent variable, whereas OPI has been considered here as a dependent variable. The dotted line and continuous line represent the effects of strong COP and weak COP, respectively. With the increase of SOD, it appears from the graph (see Figure 5) that the rate of increase of OPI will be more for the effects of weak COP compared to the effects of strong COP since it appears that the gradient of the dotted line is more than the gradient of the continuous line.

Similarly, the effects of strong COP and weak COP on the linkage H5 (PRI→OPI) is shown in Figure 6. In this graph, the independent variable PRI has been plotted on the horizontal axis, whereas the dependent variable OPI has been plotted on the vertical axis. Moreover, the dotted and continuous lines represent the effects of weak COP and strong COP, respectively, on the concerned relationship H5 (PRI→OPI). Figure 6 shows that with an increase of PRI, the rate of increase of OPI is more for the effects of weak COP compared to the effects of strong COP since the gradient of the dotted line is more than the gradient of the continuous line.

6.1. Theoretical contributions

The findings of our study extend theoretical contributions to several areas, including AI-BA opacity, operational inefficiency, contingency planning, and competitive disadvantage. First, the results reflect an AI-BA opacity through lack of governance, poor data quality, and inefficient training dimensions. These findings clarify our understanding of the dark side of AI-driven cognitive analytics from both IS and management perspectives by showing how an AI-BA opacity can adversely affect business decisions and perceived risks. Although IS scholars acknowledge that big data infrastructure can radically transform firm performance (Agarwal & Dhar, 2014; Davenport, 2018; Lycett, 2013; Grover et al., 2018; Mikalef & Krogstie, 2020), there is very limited knowledge about how to capture the components and effects of an AI-BA opacity (Ghasemaghaei, 2019). Thus, ours is the first empirical study using the RBV, DCV, and CT as theoretical foundations to model the effects of flawed technology adoption on organisational risk environment and competitive disadvantage.

To the RBV and DCV literature, we offer an avenue to address the dark side of AI by developing a robust AI integrated BA capability focusing on data, governance, and training resources. These findings are aligned with past IS research on data and system quality (Nelson et al., 2005) as well as training of the end-users (Nelson & Cheney, 1987; Motamarri et al., 2020). However, our findings extend this line of literature by conceptualising and operationalising AI-BA opacity as a holistic concept integrating data, governance, and training. Since the emergence of AI has seriously challenged the application of BA, the necessity of dynamic IS management capability is now more important by combining the complementary and cospecialization attribute of data, governance, and training to sense, seize, and transform operational efficiency and competitive advantage (Felin & Powell, 2016; Teece, 2007).

Third, this research has addressed a critical question: does AI-BA opacity directly or indirectly influence competitiveness? This is critical as the conceptualisation of whether and how an AI-BA opacity affects competitiveness is still open to debate (Ghasemaghaei & Turel, 2021). Specifically, the findings of our study show that AI-BA opacity influences operational efficiency through suboptimal business decisions and risky initiatives, which eventually results in a competitive disadvantage through negative sales growth and employee's dissatisfaction. These indirect relationships illuminate the roles of a few mediators in the model (e.g., suboptimal business decisions, perceived risks, operational inefficiency, employee's dissatisfaction, negative sales) and identify AI-BA opacity as an indirect predictor of the competitive disadvantage of an organisation. Our findings show the ripple effects of an AI-BA opacity on decision qualities, employee outcomes and firm's competitiveness. As such, this emerging technology should be assessed like all other IT artefacts considering both its "bright" and "dark" effects on firms (Tarafdar et al., 2015).

Fourth, this study identifies the moderating effect of a contingency plan on the relationship between suboptimal business decision – operational inefficiency and perceived risk – operational inefficiency. This discussion extends the dynamic capability view by identifying the effects of a contingency plan in an inappropriate AI integrated BA environment. Specifically, it highlights the importance of a contingency plan by including analytics uncertainty in the model. Although researchers have explored the contingent effect in modelling dynamic capabilities and firm performance (Schilke, 2014; Wilden et al., 2013; Karna et al., 2016), fewer studies have explored the effects of a contingency plan on operational inefficiency through suboptimal decisions and risk perceptions in this context. These findings extend the viewpoint that dynamic capabilities, such as an appropriate AI integrated BA capability aligned with a contingency plan, are required across all technology environments to tackle any turbulence.

Fifth, this study was conducted in a developing country (India) and its emerging AI-driven BA industry, allowing generalisation of the theory in a dynamic IT environment with rapid technological transformations. This is a novel context, and our findings provide a clear understanding of how an inappropriate adoption of new technology can be addressed through robust governance, upgraded training and quality data to ensure operational efficiency and sustained competitive advantage. The outcomes also demonstrate how much contingency plan influences various decision capabilities. Although contingency theory and the conditioning effects in dynamic technological environments have been investigated in reference disciplines (Tsai et al., 2013; Zhou et al., 2018), this perspective has received a very little attention in IS literature in a developing country context.

Overall, the findings of our study extend the emerging discourse and the research stream on "explainable AI" (e.g., Lebovitz et al., 2021; Rai, 2020). It opens up the avenue to comprehend the dark side of an AI by better understanding its components and effects. Unpacking such components create an exciting opportunity for learning and training in the IS field for better augmentation of decision-making by humans with the help of intelligent machines. Our findings reveal the sources of inconsistent decisions and unintended outcomes by an inappropriate AI system. Thus, these results extend the "explainable AI" body of research by exploring the components, effects, and contingency management challenges of an AI-BA opacity

6.2. Managerial implications

The findings of our study have several primary implications for managers who design and deploy AI integrated BA systems to achieve operational efficiency and competitive advantages. It is becoming increasingly important that proper deployment of an AI integrated BA system is becoming critical to replace the existing manual or heuristics-based solutions.

First, AI integrated BA development process is highly dynamic, which might result in AI-BA opacity either through lack of governance or data quality or inadequate training. Our findings provide insights for practitioners on how to avoid technical, economic, or competitive risk pertinent to AI-BA opacity. For example, our findings show that the attributes of a data set fundamentally change a model's prediction; thus, poor training data will not contribute to the development of a robust model due to various algorithmic limitations. Proper governance of the training data sets is critical to train an AI-based system to reflect attitudes, personalities, traits, and values of the target population. In addition, such deployment of AI systems should prepare employees with adequate knowledge, skills, training, and development programmes. Our findings are consistent with the recent AI failure case of Amazon, which has abandoned its AI-based recruitment system due to the unfair treatment of female applicants (Davenport et al., 2020). This is directly linked with our results on poor governance and training data quality. Thus, our findings guide managers to implement AI integrated BA in such a manner that provides beneficence to the firm as well as its stakeholders.

Second, practitioners can use our conceptual model to understand the gravity of the relationship between AI-BA opacity-suboptimal decisions and perceived risks. As our findings show, if firms underinvest in governance or training, they might not be able to develop a resilient AI-based BA system by striking a balance between risk and reward in the emerging AI revolutions. Suboptimal decisions might occur because the data being fed into the algorithms is not reliable or inadequate, or unrepresentative. Our findings on AI system–driven suboptimal decisions and risky outcomes are aligned with recent cases of Facebook's gender-biased career advertisement decisions (Lambrecht and Tucker, 2018) or Uber's and Lyft's racially biased dynamic pricing decisions (Pandey & Caliskan, 2020). Thus, our study provides guidelines to practitioners on how to diagnose AI-BA opacity-suboptimal decisions and risky outcomes in order to establish a fair, accountable, and transparent AI integrated BA.

Finally, the empirical findings from our study and our theorising based on the dark side of AI integrated BA provide fine-grained insights into the causes of operational inefficiency and competitive disadvantage. Our results provide guidance to practitioners that they must have a holistic grasp on the causal linkage between AI-BA opacity, operational inefficiency, and firm performance. Our findings show that a flawed technology strategy results in employee dissatisfaction due to a complex and nonexplainable AI system or lack of training, which is directly associated with negative sales performance and competitiveness. As such, employees need to be assured of the data quality, model transparency, and fairness of the outcome of the entire AI system in order to contribute to firm performance. In addition, our empirical findings provide the impetus for developing a contingency plan with alternative options to remove the interruption responsible for operational inefficiency. Since AI-BA opacity – operational inefficiency –competitive disadvantage is directly linked, managers should have a contingency plan to control the degrees of environmental dynamism.

Overall, the findings of our study might inspire to design, develop, and deploy the next-generation AI integrated BA system that should be beneficial, explicable, and transparent. To address the dark side of AI, our insights might help managers avoid inappropriate or unintended outcomes. In addition to contingency plans, our suggested procedural measures on holistic design and deployment might help to establish accountability of the underlying AI systems used in the organisations.

6.3. Limitations and future research directions

Like any other study, this research has also got some limitations. The data gathered for this research only focused on the service industries and did not consider manufacturing or other sectors. Hence, our survey did not cover all the sectors. Future researchers may also consider obtaining data from the manufacturing sector and can compare it with the service sector to see if there is any difference in findings for the proposed model for two different types of industries. Given the lack of time to gather data, we could collect only 355 usable responses. Future research could consider expanding the sample size to better understand the moderating impact of COP on proposed relationships with sufficient data sample. In this study, we have considered governance and management-related issues of the firms, whereas AI-related technical issues were overlooked. This could well be a component to consider by future researchers, which may necessitate investigation into the black box of emerging AI tools.

This study has dealt with issues of operational inefficiency and competitive disadvantage of the firms because of the adoption of an opaque AI-BA solution, whereas other consequential issues relating to the finance or reputation of the firms have not been dealt with. This lacuna may be plugged up by the researchers in future studies. The responses for the online survey were taken from the managers of the service sector firms of India, where some firms haven't adopted AI integrated BA solution and some others have just started to use such systems. Naturally, the inputs provided from respondents should be largely considered as the non-adopters' views. Future researchers could also think of validating the proposed model by considering responses from the adopting organisations. This study did not discuss the feasibility of an alternative or rival model as our analysis method was variance-based SEM or PLS-SEM. Since the objective of PLS-SEM is prediction rather than theory testing; thus, there was no alternative model (Akter et al., 2017; Chin, 2010; Hair et al., 2016). Future researchers may deal with this untouched avenue by analysing the model with covariance-based SEM. The explanatory power of the model was found to be 67%. Further efforts such as including some more pertinent variables and other boundary conditions along the proposed model could be made to see if the model explains improved explanatory power.

7. Conclusion

It has been noticed that IS research is found to have celebrated the benefits derived by the combined effects of AI integrated BA solution for its enormous economic and business potentials. However, there are instances where the AI integrated BA solution might delve into several misplaced assumptions where the potential dangers might be introduced by AI in the firm settings. This study has nurtured how such unintended consequences of AI integrated BA solution might impair the competitive advantage of the firm. From this study, it has emerged that effective administration of AI governance in a firm brings in sustenance towards competitiveness of that firm. On the contrary, this study shows that an ineffective AI governance would negatively influence the performance of the firm, and in that way, the firm would lose its competitiveness through operational inefficiency. The study also reveals that if the input data to the system is poor as a result of ineffective AI governance, the output of the system will lead to a suboptimal business decision and the firm will be at risk. This eventually impairs a firm's operational efficiency. Consequently, the sales growth of the firm declines and the satisfaction level of the employees also goes down. These ultimately adversely affect the competitive edge of the firm in the highly volatile technology market.

In this context, this study has suggested that there must be an appropriate contingency plan in place to overcome any unexpected and untoward incident that might occur due to the deployment of an inappropriate AI integrated BA solution. The management of the firm has to ensure that effective AI governance should be in place before the adoption of AI integrated BA solution. Further, the management also needs to ensure that proper quality of data is supplied to the system so that the output of the system is accurate. Finally, the study highlights the importance of imparting appropriate training to the concerned employees of the firm who will be using the AI integrated BA solution.

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Appendix 1: Questionnaire Summary

Construct	Dimension	Sources	Items
AI Integrated Business Analytics Opacity (ABO)	Poor Data Quality	Harlow (2018); Marshall et al. (2015); Xu et al. (2020)	**ABO1**: Data is the most important asset for any AI integrated business analytics solution. **ABO2**: Poor quality of data may lead to the development of an erroneous AI integrated business analytics solution. **ABO3**: It is difficult to get data on a real-time basis from different departments of the firm.
	Lack of governance	Winter and Davidson (2019); Lauterbach (2019); Winter and Davidson (2019)	**ABO4**: We understand that lack of governance may lead to the unsuccessful rollout of AI integrated business analytics solution. **ABO5**: We do not have a robust AI governance in place in our organisation. **ABO6**: Our organisation does not maintain the global standard of AI governance
	Inefficient Training	Cook (1973); Maity (2019); Quinney and Richardson (2014)	**ABO7**: We believe that training is an important aspect for successful rollout of AI integrated business analytics solution. **ABO8**: We do not have a robust training plan for our employees on the usage of AI integrated business analytics solution. **ABO9**: We have not been able to provide all the concerned employees adequate training on the use of AI integrated business analytics solution in our organisation.
Suboptimal Decision (SOD)		Ilyina et al. (2019); Antunes et al. (2014); Brauner et al. (2019)	**SOD1**: We understand if the AI integrated business analytics does not provide accurate information, it could be a disaster for our firm. **SOD2**: Inappropriate business decision due to erroneous AI integrated business analytics solution is a risk to our firm. **SOD3**: We believe the AI integrated business analytics solution may not provide accurate information under all the circumstances.
Perceived Risk (PRI)	Technology Risk	Masakowski (2020); Yeoh (2019); Khaksar et al. (2019); Hartmann and Lakatos (1998); Marks (2008)	**PRI1**: We do not have enough technology competency for fully adopting AI integrated business analytics solution in our firm. **PRI2**: We think AI as a technology cannot be used for important decision-making purpose. **PRI3**: We believe AI integrated business analytics solution may be a technology risk for our firm.
	Security Concern	Yeoh (2019); Klatt et al. (2011); Post and Kagan (2006); Vermeulen and Von Solms (2002)	**PRI4**: AI integrated business analytics solution may pose security challenges to our organisation. **PRI5**: Appropriate security should be in place before organisation can fully adopt AI integrated business analytics solution. **PRI6**: We do not have appropriate security mechanism to fully adopt AI integrated business analytics solution in our firm.
Contingency Plan (COP)		Hall et al. (2012); Simpkins (2009); Jordan (1999)	**COP1**: Our organisation does not have any special contingency plan for the AI integrated business analytics solution. **COP2**: Contingency plan is important for successful conduct of operation for any organisation. **COP3**: We do not have top level leadership support for a separate contingency plan for AI integrated business analytics solution.
Operational Inefficiency (OPI)		Papadopoulos and Karagiannis (2009); Croom et al. (2018); Kuo et al. (2010)	**OPI1**: Improper business decision will lead to operational inefficiency **OPI2**: Lack of business continuity plan will have an adverse impact to the operation of our firm. **OPI3**: There is a risk of using AI integrated business analytics solution in our organisation which may result operational inefficiency.
Negative Sales Growth (NSG)		Bolander et al. (2017); Claro and Ramos (2018); Rapp et al. (2020)	**NSG1**: Organizational inefficiency due to adoption of inappropriate AI integrated business analytics solution may lead to negative sales growth. **NSG2**: Our organisation may lose its market share due to negative sales growth. **NSG3**: Inappropriate business decision due to erroneous AI integrated business analytics solution will lead to negative sales growth.
Employee Dissatisfaction (EDS)		Dustin and Belasen (2013); Underwood (1982); Amissah et al. (2016)	**EDS1**: We believe there is a close relationship between erroneous AI integrated business analytics solution and employee dissatisfaction. **EDS2**: In our opinion employees will be more dissatisfied if there is operational inefficiency in the firm due to erroneous AI integrated business analytics solution. **EDS3**: Inappropriate usage of AI integrated business analytics solution will lead to employee's dissatisfaction.
Firm's Competitive Disadvantage (FCD)		Karabag et al. (2014); Sun and Pang (2017); Cerrato and Depperu (2011)	**FCD1**: We believe that if firms do not have a robust AI integrated business analytics solution, then the firms will have competitive disadvantage. **FCD2**: Firms which do not have accurate AI integrated business analytics solution will suffer from competitiveness. **FCD3**: We may lose our firm's competitiveness if we use an erroneous AI integrated business analytics solution