Big data analytics adoption model for small and medium enterprises

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Abstract

Purpose – Big data analytics (BDA) is recognized as a turning point for firms to improve their performance. Although small- and medium-sized enterprises (SMEs) are crucial for every economy, they are lagging far behind in the usage of BDA. This study aims to provide a single and unified model for the adoption of BDA among SMEs with the integration of the technology–organization–environment (TOE) model and resource-based view.

Design/methodology/approach – A survey of 112 manufacturing SMEs in Iran was conducted, and the data were analysed using structural equation modelling to test the model of this study.

Findings – The results offer evidence of a BDA mediation effect in the relationship between technological, organizational and environmental contexts, and SMEs performance. The findings also demonstrated that technological and organizational elements are the more significant determinants of BDA adoption in the context of SMEs. In addition, the result of this study confirmed that BDA adoption could enhance the financial and market performance of SMEs.

Practical implications – Providing a single unified framework of BDA adoption for SMEs enables them to appreciate the importance of most influential elements (technology, organization and environment) in the adoption of BDA. Also, this study may encourage SMEs to be more willing to use BDA in their businesses.

Originality/value – Although there are studies on BDA adoption and firm performance among large companies, there is a lack of empirical research on SMEs, in particular, based on the TOE model. SMEs differ from large companies in terms of the availability of resources and size. Therefore, this study aimed to initiate a conceptual framework of BDA adoption for SMEs to assist them to be able to take advantage of the adoption of such technology.

Keywords SMEs, Big data analytics, Firm performance, Technology adoption, Resource-based view, TOE model

Paper type Research paper

1. Introduction

The current world, which is prevailed by globalization, knowledge, fast speed of digitalization and information dissemination and competition, has transformed the mode of businesses (Bouwman et al., 2018). This modern technological era is compounded with a high amount of financing in computerizing and data processing in different industries. With these technological advancements, the utilization and implementation of new Information Technology (IT) applications and techniques become a considerable strength for
socioeconomic changes (Bresnahan and Yin, 2017; Mariadason, 2014; Tambotoh et al., 2015). Therefore, the adoption of innovative technologies can produce more business advantages and opportunities not only to large corporations but to small- and medium-sized enterprises (SMEs) as well. Even SMEs are looking for ways and methods to enrich their competitive positioning in the market and enhance their productivity (Premkumar, 2003; Ghobakhloo et al., 2012).

In the light of digitalization, where everybody uses new digital technologies such as smartphones and social media, technology in terms of raw data has become accessible primarily to grasp, keep, analyze and use at a lower cost (Alsghaier et al., 2017). Thus, a ubiquitous and ever-increasing digital record, commonly termed big data, is getting generated by each individual around the world (Müller et al., 2016). Big data has currently been acknowledged as one of the pillars of future technology and has the potential to offer firms with excellent business value (Raguseo and Vitari, 2018). Despite the many benefits of big data analytics (BDA), less research has taken place about how companies can adopt it and create business value from such a technology. Thus, there is a lack of understanding on how businesses deal with the process of BDA implementation and value generation (Mikalef et al., 2019).

Recent studies have also claimed that a notable number of firms cannot be prosperous to leverage value from the opportunities that BDA may produce for their companies, and some scholars even denied the notion that companies could gain performance enhancement through BDA (Mikalef et al., 2019). As such, there might be an inadequate understanding and contradictory views about how businesses can use BDA and benefit from such investments (Wamba et al., 2017). Also, the promises of BDA are not adequately explored by companies such as SMEs (Mikalef et al., 2019). This study investigates how SMEs benefit from business values of BDA adoption. It aims at providing a single and unified model for the adoption of BDA among SMEs with the integration of the technology–organization–environment (TOE) model and resource-based view (RBV) of the firm. By doing so, the more influential context in terms of TOE for the adoption of BDA among SMEs could be determined. Subsequently, the impact of BDA adoption on the performance of SMEs was examined. Finally, this study evaluates the role of BDA as a mediator between TOE contexts and firm performance. More precisely, this study addresses the following research questions:

RQ1. To what extent could TOE contexts affect the adoption of BDA among SMEs in Iran?

RQ2. What is the impact of BDA adoption on SMEs’ performance? And

RQ3. To what extent does BDA adoption mediate the direct relationships between TOE-based factors and business performance among Iranian SMEs?

2. Big data analytics and small and medium enterprises

Like entrepreneurs, SMEs are risk takers and innovative (Dana and Dana, 2005). What makes them distinguished from other companies is their entrepreneurial growth-oriented mind (Dana, 1995). Furthermore, SMEs act as the main element of economic growth by creating job opportunities and being innovative and productive (OECD, 2017; Talebi et al., 2012; Singh, 2019). Moreover, in a globalized environment, one of the effective methods to reduce poverty and inequality in developing countries is developing and improving the position of SMEs in the marketplace (Talebi et al., 2012).
According to Emami and Dimov (2017), entrepreneurs tend to make an independent decision and be creative to add value to the customers and consequently, to the economy. Entrepreneurs should look for the opportunity to increase their competitive advantage in the market by being more innovative by changing the current status of the market and adding new values to the marketplace (Emami, 2017; Emami and Khajeheian, 2019). Therefore, adopting new technology within SMEs could be one of the critical strategies to upgrade their status in the marketplace and become more innovative and productive (Iqbal et al., 2018; Singh, 2019). The attention of current scholars toward SMEs to help these enterprises to be innovative and to be able to take advantage of new technologies has been increased. For example, in the area of cloud computing adoption (Asiaei and Rahim, 2019), mobile marketing adoption (Eze Sunday et al., 2019), and mobile commerce (Nayati Utami et al., 2019).

BDA is a newly emerged strategy for SMEs growth, which enables them to make better decisions about market and customers’ needs by relying on analytical tools. That also will help them to increase their competitive status in the market (Sen et al., 2016). According to OECD (2017), BDA is a turning point to the business processes development, so there is a need for SMEs to think, seriously, about BDA adoption. SMEs can derive value from voluminous data by receiving the assistance of big data service providers. The adoption of big data in SMEs can be fruitful in tackling the important challenges of businesses (EPU, 2017). Using big data and its analytical techniques are not only for large enterprises.

Nowadays, small businesses also can use the advantages and hidden values of the high amounts of online and offline data to make reliable decisions in line with the objective of their businesses (Ogbruokiri et al., 2015). Embracing big data could be useful for SMEs, as this technology can improve the confidence of SMEs by implementing real-time solutions to issues that every business may encounter (Sen et al., 2016). The use of BDA enables SMEs to have better performance, as they are more flexible than large companies (Ogbruokiri et al., 2015). It is reported that competition is one of the main reasons for SMEs to adopt BDA (Tien et al., 2020). The acute sense of competition among SMEs in the market would force them to embrace the adoption of BDA to increase operational performance and stay competitive (Malaka and Brown, 2015; Tien et al., 2020). In the case of Iran, the speed of creating big data is rapidly increasing, and that is a need for all Iranian companies, including SMEs, to know how to take advantage of big data values and how direct it to the improvement of their performance (ITRC, 2018).

While many large organizations have long been utilizing big data to enhance their competitiveness (Mandal, 2018), SMEs lagged in using BDA technologies (Tien et al., 2020; Coleman et al., 2016). Previous studies also highlight this point that SMEs are expected to consider adopting BDA in their businesses (Iqbal et al., 2018; Maroufkhani et al., 2019). Considering the role of SMEs in emerging economies, the adoption of BDA as a new type of innovation among SMEs should not be understated. According to Maroufkhani et al. (2019), most of the current literature emphasized the importance of BDA in large companies (Akter et al., 2016; Wamba et al., 2017; Wang et al., 2018).

However, majority of SMEs are reluctant to utilize big data techniques in their businesses, or they fail to have practical use of BDA investments, which is mainly due to lack of understanding and knowledge about big data (Oussous et al., 2018; Iqbal et al., 2018). The failure of BDA is often the result of big data’s unique resource capabilities. For example, deprived IT infrastructure, inappropriate skills, fragile support from top management, inadequate technologies to support high volume unstructured data, blurred strategy to align business and IT strategy and limited financial support lead SMEs not willing to adopt new technologies such as BDA (Shin, 2016; Coleman et al., 2016; Christina and Stephen, 2017).
Due to the challenges and the scarcity of BDA adoption within SMEs, knowledge on how SMEs would be able to adopt big data and take advantage of its analytical tools becomes essential. Drawing on the RBV, this paper aims to examine the impact of each context of the TOE model on BDA adoption, and the mediating role of BDA adoption in the relationship between TOE contexts and firm performance.

The paper is organized as follows: the next section discusses the conceptual model and hypothesis development followed by the research methodology and empirical findings. Finally, the discussion and conclusion sections outline the research and practical implications and conclude the study.

3. Conceptual model and hypotheses
This study uses the TOE model to assess BDA in SMEs. The hypotheses and the model are depicted in Figure 1. The dotted lines show the indirect effects. The TOE model is prevalent in scrutinizing issues related to technology or innovation adoption, such as the adoption of BDA (Garmaki et al., 2016). The model, established by Tornatzky et al. (1990), was developed to be a consolidative framework, which offers a general theoretical foundation in the adoption/diffusion of technology in businesses. It generally measures different technological, organizational and environmental factors that assist the process of adoption/diffusion of various technologies (Ghobakhloo et al., 2011a). TOE model is reconcilable with the diffusion of innovation theory, as it concentrates on both internal and external features.
of organizations in terms of technological, organizational and environmental elements (Baker, 2011).

Several reasons support the choice of applying TOE in the current study. First, the TOE model includes the environmental context, ignored by the Innovation Diffusion Theory. The incorporation of the environmental context increases the power of the TOE model to be superior to the latter and discuss intra-organization innovation adoption much better than others (Maduku et al., 2016). Second, the TOE framework explains how the technological, organizational and environmental contexts affect the adoption of technology and also how these three contexts affect the decisions and performance of companies (Baker, 2012). Third, the TOE model is a flexible contextual theory which can be used in different contexts and allows researchers to include and exclude the technological, organizational and environmental factors that are in line with the context of their studies (Grant and Yeo, 2018). Fourth, the TOE model renders a more strong empirical and theoretical basis and support for organizational level studies (Alshamaila et al., 2013b). Finally, the TOE model has been recognized as the most frequently-used technology adoption theory among scholars (Oliveira and Martins, 2011; Hsu et al., 2014; Maduku et al., 2016). Therefore, the TOE model is the most applicable theory for the context of SMEs, as it delivers rich and vibrant views to deal with SMEs (Awa et al., 2015).

This study draws on RBV and capability building view to examine the effect of BDA adoption on SMEs’ performance. RBV is suitable in acknowledging firm technological activities through the theoretical standpoints of organizational resources and capabilities (Ramdani and Kawalek, 2007). A focal point of RBV is that the firm performance depends highly on the elements or qualities of a firm’s capabilities or resources (Barney, 1991). Grounding on the RBV as well as capability-building theory, BDA denotes a capability or an intangible resource for firms by which companies gain business value and improve their performance.

3.1 Technological context
This context can have a significant effect on technology adoption in SMEs (Dosi, 1990). Relative advantage, compatibility, complexity, risk and insecurity, trialability and observability constitute the context of technology that influences BDA adoption in SMEs.

Rogers (1983) has defined the relative advantage “as the degree to which an innovation is perceived as being better than the idea it supersedes”. Prior studies such as Ramdani et al. (2013) and Priyadarshinee et al. (2017) propose that relative advantage is a crucial element of the technological context that is capable of encouraging or discouraging the adoption of technology. The primary decision-makers of enterprises evaluate the consequences or advantages of applying BDA to make sure if this technology has a relative advantage over current systems (Alshamaila et al., 2013a; Chen et al., 2015). In a highly competitive marketplace, the benefits that BDA may generate for companies make significant motivations for adopting this technology.

Compatibility is an imperative leading element for technology and innovation adoption (Chen et al., 2015). Rogers defined compatibility as “the degree to which the innovation is perceived as consistent with the existing values, past experiences, and needs of the potential adopter” (Agrawal, 2015). Similarly, in Tornatzky and Klein’s (1982) study, compatibility was measured as one of the most important determinants in the post-adoption phases of innovation diffusion. The main concern of business founders might be that if the adopted innovation is consistent with values and the history of their corporations (Rogers, 1983). Consequently, it is essential for SMEs that innovation is consistent with their existing
values and needs. Therefore, the compatibility of technology adoption may reflect its congruity with the culture and business practices of an organization (Zhu et al., 2006).

According to Lee (2004), complexity is the degree to which an innovation is perceived as relatively difficult to understand and use. Chen et al. (2015) testified that technology innovation would be less likely to be implemented if it is perceived as being more ambitious and challenging to implement. Adopting a new technology may put SMEs into challenges, for example, altering the processes in which they work together. To promote the chance of adoption, the new technology must be easy to use (Rogers, 2003). Employees have or gain knowledge about new technology either. The more new technology is complex, the more risk involved in the process of adoption. Thereby decision-makers will be in a dilemma about adopting the innovation (Sahin, 2006). Some of the current studies coined that complexity is a substantial factor in the adoption of an innovation (Alshamaila et al., 2013a; Premkumar and Roberts, 1999).

Risk could be defined as the degree to which the results of incorporating an innovation in an organization might be insecure (Tiwana and Bush, 2007). A study regarding cloud computing adoption within SMEs (Harindranath et al., 2008) indicated that cloud computing innovation is hugely dependent on the level of risk. The risk may imply that there should be a lack of sufficient understanding about a specific innovation which could lead to less predictable outcomes. As discussed before, the cloud is a host for big data. Therefore, the privacy and security act as predictors of BDA, which may influence its adoption. It is argued that the primary concern of business owners when the adoption of cloud computing services comes up, is privacy and security (Ostlund, 1974). The significant reason for enterprises’ concern is data management and storage because users of cloud computing give the cloud supplier full control over their data and they will be worried whether the supplier exercise proper care of their business, secure the data, and do backups for them (Alshamaila et al., 2013a). Priyadarshinee et al. (2017) figured out that the security concern is one of the principal factors when companies come to the idea of adoption of cloud computing and big data as the companies have to share their data with third parties. Nevertheless, this can be addressed by building a trustable relationship with service suppliers.

From this point of view, security concern refers to the risks that occur in outsourcing. In other words, these are the risks linked to the use of third-party tools and assistance for big data solution (Benlian and Hess, 2011) or cloud computing services adoption (Priyadarshinee et al., 2017). Generally, companies who are willing to use the advantages of big data in their businesses may need to begin with outsourcing the whole initiatives of big data or part of it. For example, the result of a study worked on BDA adoption indicates that most of the companies use outsourcing, first, as they still suffer from the lack of enough capability to build and sustain big data environment within their own businesses, second, due to newness of big data related innovations (Wood, 2013). However, the requirement of outsourcing may raise the issue of security or privacy. Since outsourcing requires companies to share their data with vendors and external suppliers, there is risk of losing the control over their information. This study concludes that the factor of risk and insecurity will significantly influence BDA adoption.

Trialability is the extent to which an IT innovation is possible to try (Salleh and Janczewski, 2016). Priyadarshinee et al. (2017) have defined trialability “as the degree to which an innovation may be experimented with on limited basis.” Trialability is one of the key factors for early adopters, including SMEs (Moore and Benbasat, 1991; Rogers, 2003; Moghavvemi et al., 2012) because, from the initial stage, they know how effective the innovation is. Therefore, it can be a chance for early innovators to reduce the level of insecurity (Ramdani and Kawalek, 2007). According to Alshamaila et al. (2013a), the more
quickly the innovation can be exposed, the more easily and speedy it can be adopted. Rogers (2003) proposes that trialability is the most vital factor that affects the adoption of the internet and new online technology among academia. For example, Murphy (2005) examined Wi-Fi adoption among academy members and figured out that those who did not have their device lost the opportunity of experimenting with Wi-Fi technology, which resulted in a slighter rate of adoption. The BDA under consideration in this paper is recently novel to the SMEs. As a result, trialability is predicted to be appropriate.

Observability argues that “the degree to which the results of an innovation are visible to others” (Jeyaraj et al., 2006). Observability promotes and encourages innovation adoption within firms. For example, Lu et al. (2009) studied the adoption of cellular phones in Hong Kong and found that among other technological factors, only observability stayed to have a significant effect on the adoption. However, in the context of SMEs, observability is the only attribute of technological factors to have no positive influence on the adoption of IT innovations (Rogers, 2003) hence the promising light of BDA. In short, all of the abovementioned factors are considered a technological context. Therefore, we suggest the following hypothesis:

H1. The technological context influences the adoption of BDA in SMEs.

3.2 Organizational context
In this study, top management support and organizational readiness represent an organizational factor that influences BDA adoption in SMEs. This context is claimed to have a high impact on SMEs’ adoption of BDA since previous scholars such as Wei (2001) revealed that organizational context is a primary factor of the adoption of enterprise applications in SMEs.

Ramdani and Kawalek (2007) define top management support as the degree to which managers comprehend and embrace the technological capabilities of a new technology system. In addition, Ramdani et al. (2013) define top management support as the positive attitude of CEOs towards technology adoption. Previous studies such as Sanders (2008), Scupola (2009), Jeyaraj et al. (2006) and Huynh et al. (2012) have advocated that top management support is one of the key determinants of organizational innovation adoption so that adoption of a technology without top management support does not have the chance of successful implementation. For example, in the context of SMEs, top managers are less likely to adopt new technologies (Chen et al., 2015; Alshamaila et al., 2013a). Top management in all organizations, including SMEs, can encourage change by collaboration and strengthening values through a joint vision for the company (Ramdani and Kawalek, 2008).

It is believed that once top managers are optimistic about the possible benefits of technology adoption to the enterprise, they will be more likely to take action to defend and support the adoption of a new system (Ramdani and Kawalek, 2007). A constructive attitude of owners can bring up the confidence that adequate resources will be allocated for adopting the new technology (Thong, 1999; Liang et al., 2007). By providing support, top managers can play the facilitator role for arranging the process of change in terms of organizational norms, values, and cultures, which enables other members of an organization to accept and adopt the new technology (Premkumar and Potter, 1995; Vahtera, 2008; Karahanna and Preston, 2013). Top management role can be critical for building a supportive atmosphere for the adoption of new technologies (Kearns and Sabherwal, 2006; Lim et al., 2013).

According to Premkumar and Roberts (1999), organizational readiness refers to the extent to which the required organizational resources are available to utilize technology like
BDA. That is reported by Eder and Igbaria (2001) that the level of supports that top management can offer for organizational IT initiatives is dependent on the availability of the company’s resources. In further studies, organizational readiness is defined as the capability of companies in managing and investing for the adoption of new technology by providing sufficient resources such as technical IT capability and expertise (Chen et al., 2015). In the context of SMEs, studies indicate that financial shortage and lack of technical knowledge are realized as two of the main elements that hold back information system (IS) development in small businesses (Taxman et al., 2014). Recent literature indicated that a prosperous adoption of new technology is severely influential by the degree of preparation of organizations for the technology (Yoon and George, 2013). Cragg and King (1993) reported that companies are unable to appropriately apply and maintain a new system such as information sharing system if they do not devote sufficient organizational assets (e.g. financial supports and technical skills). It can apply to other types of technology innovation. Therefore, we suggest the following hypothesis:

H2. The organizational context influences the adoption of BDA in SMEs.

3.3 Environmental context

In the current study, competitive pressure, external support and government regulations are the environmental factors, as a unified environmental context, which influences BDA adoption in SMEs. Based on the definition which Oliveira et al. (2014) have developed, “competitive pressure refers to influences from the external environment that prompt the organization to use BDA.” It can be the pressure that comes to a company from its customers, suppliers and competitors.

Tsai et al. (2013) determined competitive pressure as one of the preeminent antecedents of IS innovations adoption within firms. Competition in an industry is mostly perceived to have a positive impact on the adoption of IS innovations (Chen et al., 2015). Jeyaraj et al. (2006) asserted that it should be taken into account by companies that they can adopt new technologies to compete in the market place. It can be considered a kind of organizational strategy. There is other evidence that competitive pressure can be an adoption driver (Gatignon and Robertson, 1989; Premkumar and Ramamurthy, 1995; Grover, 1993). Notably, Iacovou et al. (1995) stated that competition imposes too many pressures on companies to seek new options to upgrade their production. For small enterprises, Crook and Kumar (1998) discovered that competitive pressure could be a crucial predictor for innovation adoption. Also, this predictor can be one of the practical factors in outsourcing, where companies crowdsource their IT infrastructure to enhance their effectiveness (Leibenstein, 1976). That is supposed that competitive pressure can assist firms in boosting up their market share by rendering lower prices (Premkumar and Roberts, 1999).

In the context of SMEs, Lacity and Willcocks (1998) reported in their study that the more firms feel that they are under pressure to compete, the more they will adopt new technology. Based on the summary by Majumdar and Venkataraman (1993), out of the ten studies listed, five of them reported that competition significantly influences technology adoption in SMEs.

External support has been defined as the extent to which vendors or third-parties can provide technological support for companies to adopt important innovation (Al-Qirim, 2007). External support from or outsourcing has been found as one of the critical drivers of IS innovation success (Grandon and Pearson, 2004), which can positively influence IS innovation adoption (Premkumar and Roberts, 1999). The more outsourcing and third-party support increase, the more enterprises are likely to adopt new information system innovations. The willingness of companies to adopt an IS innovation depends on how they
perceive the vendors, and third-parties’ support is available (DeLone, 1988). Premkumar and Roberts (1999) claimed that firms could increase their innovation adoption abilities by taking advantage of experiential learning advertised or offered by their supplier, which at the end may lead to successful firm’s innovation adoption (Ramdani et al., 2009).

The last factor of the TOE model in this study is government regulation, which has been also realized as another imperative element in innovation adoption (Weigelt and Sarkar, 2009; Frambach and Schillewaert, 2002; Williamson, 1983). The regulations imposed by authorities of governments yield firms to look for technological alternatives. Government regulations can be in terms of promotions and restrictions. Sometimes these regulations may encourage firms to adopt a specific type of new technology. In contrast, sometimes, it may prohibit firms from adopting innovations in certain areas (Umanath and Campbell, 1994; Li, 2008).

Tornatzky et al. (1990) asserted that sometimes government regulations for the adoption of technology require businesses to have some preconditions, such as some specialized standards, in place that may impose higher transaction costs on firms to adopt a favourable technology. Therefore, for example, Stieninger and Nedbal (2014) suggested that governments can encourage companies for innovation adoption, particularly for e-business adoption, by supporting firms through the appropriate imposition of tax laws and beneficial firm development policies. According to previous studies on the role of external support in technology adoption, we propose the following hypothesis:

**H3.** The environmental context influences the adoption of BDA in SMEs.

### 3.4 Big data analytics and firm performance

The firm performance consists of financial and market performance together (Delmas, 2002). Financial performance is associated with revenue growth and profitability, whereas market performance refers to upgrading the position of firms in the market place to gain their competitive advantage (Xu et al., 2004; Ren et al., 2017). Profitability, market share, growth, innovativeness, cost reduction, fast delivery time as compared to competitors are representative of the potential value resulted from the BDA adoption (Mikalef et al., 2019). According to Müller et al. (2018), the business value of BDA has a direct effect on firm performance. Also, some studies found a positive relationship between BDA adoption and organizational performance (Mikalef et al., 2019; Raguseo and Vitari, 2018; Germann et al., 2014). For example, the optimization of price and profit intensification (Wamba et al., 2017); sales maximization, financial productivity, and market share (Wixom et al., 2013); and return on investment (ROA) (Schroeck et al., 2012; Manyika et al., 2011; Barton and Court, 2012). According to McAfee et al. (2012), big data is a technological capability that enhances the financial welfare of companies.

Ramaswamy (2013) in their research, in the context of healthcare, claimed that gaining capability in BDA will help firms to stay competitive through cost reduction. For instance, it will assist them in reducing the amount of waste and fraud. Also, it can help companies to improve the level of care quality, such as safety in treatment. A study by Raut et al. (2019) demonstrates that BDA can enhance companies’ performance via boosting productivity, either tangible such as less paper reporting or intangible productivity like firm reputation. Consequently, an organization that builds more excellent BDA capability would be able to get the best out of its performance. It can be done by facilitating the process of BDA capability and identifying the most significant factor in terms of technology, organization and environment. That is to say, having a superior firm performance in a data driven system would be originated from a perfect combinations of all resources, for example,
organizational (BDA management), physical (IT infrastructure), and human (analytical knowledge) resources which should be unique and inimitable (Srinivasan and Arunasalam, 2013; Wixom et al., 2013). Hence, a significant investment in BDA enables a firm to enhance its performance.

BDA provides companies with the opportunity to obtain administrative understanding from the hidden data to build an agile businesses. Those firms with effective use of big data are more capable of transforming data into meaningful deliverable information in different parts of the organization. They can facilitate the process of marketing improvement, product/service and human resource development, and organizational operation enhancement, eventually enabling organizations to be more innovative (Barton and Court, 2012). In this sense, we propose the following hypotheses:

$$H4. \text{ BDA adoption influences the financial performance of SMEs.}$$

$$H5. \text{ BDA adoption influences the market performance of SMEs.}$$

3.5 Mediating role of big data analytics in the relationship between TOE model and firm performance

TOE factors, as the predictors of organizational innovation adoption, can improve the performance of companies by assisting the companies in identifying the most significant factor of a successful adoption. Successful adoption of any IT/IS innovation leads to effective business performance (Akter et al., 2016; Dutta and Bilbao-Osorio, 2014). Based on the TOE model, a company can effectively adopt innovative initiatives if the technological, organizational, environmental factors can be identified (Fillis et al., 2004; Ahani et al., 2017). According to Aboelmaged (2014), the TOE model can show how the appropriate drivers of innovation adoption influence firm performance. TOE context can increase sustainability performance and competitive capabilities (product cost, quality, flexibility, or delivery) of SMEs in the manufacturing sector through the adoption of an innovation such as sustainable manufacturing practices (SMP). Aboelmaged (2018) concur with the argument, and he further investigated the relationship between the TOE context, precisely the element of technology and environment, on sale growth as a firm performance measurement. The result indicated that the environmental element, as compared to the technological one, could significantly affect the growth of sales in the service sector.

Other studies have found that there a positive relationship between Internet technologies such as website technologies and firm performance (Schoenherr, 2012; Yeo, 2016; Meroño-Cerdan and Soto-Acosta, 2007; Meroño-Cerdan and Soto-Acosta, 2005). A study by Soto-Acosta et al. (2016) shows that innovation adoption in companies can be considered as a mediating variable in the relationship between the use of e-business and firm performance. Grounded in RBV, Ren et al. (2017) have statistically confirmed that BDA could increase the performance of firms and also would play a mediating role in the relationship between data and information quality and firm performance. Additionally, Raut et al. (2019) found that BDA adoption could be a mediator between several determinants of BDA adoption in the manufacturing sector and sustainable business performance.

Following Baron and Kenny (1986), and as a more recent approach on mediation test by Zhao et al. (2010), there should be a direct relationship between an independent variable and dependent variable to test a mediating effect within a relationship. In this line, the direct effect of TOE factors and firm performance delineates that a technology adoption such as BDA adoption act as the mediating variable. One of the evidence is the result found by Tsou and Hsu (2015), which is relatively similar to the context of the current research in
technology and innovation adoption. Another study developed by Grant and Yeo (2018) argued that TOE contexts would affect the performance and decisions of firms in the context of Information and Communication Technologies. Moreover, a recent study Narwane et al. (2020) empirically confirmed that innovation such as the cloud of things could be a mediator between its determinants and SMEs’ performance.

Thus, this study attempted to take one step further and evaluate the mediating role of BDA adoption in the relationship between TOE contexts with firm performance. The review of the literature in this study demonstrated that empirical analysis of the mediating role of BDA remains sparse. Therefore, the focus of this study is theoretical development, based on the existent evidence available, to explain the mediating effect of BDA adoption between TOE contexts and firm performance in a single framework. Therefore, this study proposes the following hypotheses:

H6. The BDA adoption has a mediating effect on the relationship between the technological context and the financial performance of SMEs.

H7. The BDA adoption has a mediating effect on the relationship between the technological context and the market performance of SMEs.

H8. The BDA adoption has a mediating effect on the relationship between the organizational context and the financial performance of SMEs.

H9. The BDA adoption has a mediating effect on the relationship between the organizational context and the market performance of SMEs.

H10. The BDA adoption has a mediating effect on the relationship between the environmental context and the financial performance of SMEs.

H11. The BDA adoption has a mediating effect on the relationship between the environmental context and the market performance of SMEs.

4. Methodology
4.1 Scale development and sampling
To test the hypotheses developed in this study, we distributed a questionnaire to a sample of Iranian manufacturing SMEs located in industrial parks, namely, Sahmsabad and Abbasabad, of Tehran province. The measurement instrument (questionnaire) consisted of two sections. The first section evaluates the overall profile of respondents. For the second section, we employed a five-point Likert scale, with responses ranging from 1 representing “strongly disagree” to 5 “strongly agree,” which all items obtained from previous studies.

Before sending the final questionnaire, a few initial tests were performed to ensure the accuracy of the analysis. First, a pilot study was conducted on a sample of 30 firms to test the ambiguity of the questions in the instrument, and to confirm the reliability and validity of the measurements. Based on the comments by experts in the initial stage, a few measurement items were eliminated, and some questions were rephrased for better clarity. Eventually, the questionnaire was revised by replacing shorter and simpler questions to improve the reliability of responses. The final version of the questionnaire is shown in Appendix.

The appropriate sample size for structural equation modelling (SEM) using partial least squares (PLS) should be between 100 to 200 (Kline, 2005). In addition, Bryant and Yarnold (1995) recommended that the number of the sample has to be five times the number of variables. Hatcher (1994) also pointed on the use of “rule of 100” as the minimum sample size
or not less than five times the number of variables, whichever is higher. Therefore, we distributed 161 questionnaires among Iranian SMEs operated in manufacturing sectors and located in industrial parks of Tehran province. One hundred twelve questionnaires were found suitable to be used in the analysis, as they are able to evaluate their experience of BDA adoption and oversee the process of adoption in their businesses. As shown in Table 1,

<table>
<thead>
<tr>
<th>Education</th>
<th>(%)</th>
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</thead>
<tbody>
<tr>
<td>Primary qualification</td>
<td>4</td>
</tr>
<tr>
<td>Secondary qualification</td>
<td>7</td>
</tr>
<tr>
<td>Diploma</td>
<td>34</td>
</tr>
<tr>
<td>Undergraduate degree</td>
<td>53</td>
</tr>
<tr>
<td>Postgraduate degree (Master/PhD)</td>
<td>3</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Age</th>
<th>(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>18–25 years old</td>
<td>4</td>
</tr>
<tr>
<td>26–33 years old</td>
<td>31</td>
</tr>
<tr>
<td>34–41 years old</td>
<td>38</td>
</tr>
<tr>
<td>42–49 years old</td>
<td>19</td>
</tr>
<tr>
<td>50 years old or older</td>
<td>7</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Gender</th>
<th>(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>90</td>
</tr>
<tr>
<td>Female</td>
<td>10</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Number of employees</th>
<th>(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1–10 employees</td>
<td>14</td>
</tr>
<tr>
<td>11–49 employees</td>
<td>60</td>
</tr>
<tr>
<td>50–99 employees</td>
<td>21</td>
</tr>
<tr>
<td>100–149 employees</td>
<td>5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sector type</th>
<th>(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food and beverages</td>
<td>13</td>
</tr>
<tr>
<td>Wood and wood products (except furniture)</td>
<td>2</td>
</tr>
<tr>
<td>Chemical</td>
<td>9</td>
</tr>
<tr>
<td>Rubber and plastic</td>
<td>9</td>
</tr>
<tr>
<td>None-metal minerals</td>
<td>16</td>
</tr>
<tr>
<td>Basic metals</td>
<td>12</td>
</tr>
<tr>
<td>Fabric metals</td>
<td>10</td>
</tr>
<tr>
<td>Machinery and equipment</td>
<td>15</td>
</tr>
<tr>
<td>Office equipment</td>
<td>2</td>
</tr>
<tr>
<td>Electrical machineries and equipment</td>
<td>6</td>
</tr>
<tr>
<td>Radio, TV and communication tools</td>
<td>2</td>
</tr>
<tr>
<td>Optical and medical instrumental and watch</td>
<td>4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Position</th>
<th>(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Executive/senior manager</td>
<td>42</td>
</tr>
<tr>
<td>Chief executive manager/owner</td>
<td>58</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Big data experience</th>
<th>(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 1 year</td>
<td>10</td>
</tr>
<tr>
<td>1–2 years</td>
<td>46</td>
</tr>
<tr>
<td>2–3 years</td>
<td>30</td>
</tr>
<tr>
<td>3–4 years</td>
<td>12</td>
</tr>
<tr>
<td>4+ years</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 1. Profile of survey respondents
out of 112 valid questionnaires, more than half of the respondents were owners or CEOs of the companies. The sample of respondents, which is male-dominated, has tertiary education of at least one for every two individuals. Based on the results obtained in Table 1, the majority of the SMEs, more than three quarters, have had between 1 to 3 years of experience in BDA adoption.

5. Empirical findings
To perform the structural equation modelling technique, a two-step procedure was applied (Soto-Acosta et al., 2016). The first step was to estimate the measurement model, and the second step was testing the structural model. The measurement model was constructed to confirm the reliability, convergent validity, and discriminant validity of the construct. The second step was to verify the structural model by testing the hypotheses proposed in this study.

To calculate the second-order hierarchical TOE-BDA model, this study applied Partial Least Squares-Structural Equation Modelling (PLS-SEM) because it determines hierarchical model by eliminating the ambiguity of irrelevant solutions employing its flexible assumptions (Chen et al., 2015; Anderson and Gerbing, 1988). PLS path modelling calculates the hierarchical model with less complexity (Hair et al., 2011; Hulland et al., 2010). For instance, Edwards (2001) developed a second-order TOE model, using PLS path modelling, to estimate the impact of technological, organizational and environmental context for the adoption of enterprise applications in SMEs. Besides, PLS can handle comparatively small sample sizes (Wetzels et al., 2009).

There are two different ways to calculated hierarchical modelling, which depend on the relationship among latent variables and manifest variables, that is, hierarchical-reflective modelling and hierarchical-formative modelling. In the reflective model, the latent variables reflect the manifest variables (LVs → MVs), while in the formative one, the manifest variables form the latent variables (MVs → LVs). When second-order hierarchical latent variables involved, four types of modellings can be named based on the relationship between the first-order latent variables and their manifest variables and the second-order latent variables and the first-order latent variables (Chin, 1998).

As outlined in Ren et al. (2017), the reflective–reflective Type I model and the formative–formative Type IV model are the conventional reflective and formative models explained above. In the formative–reflective Type III model, the higher-order construct is a concept of a few formative lower-order constructs, and in the reflective–formative Type II model, the lower-order concepts are reflective constructs that form a general construct. In this study, the reflective lower-order concepts form the TOE contextual constructs. Hence, the proposed TOE-BDA model is a hierarchical reflective–formative Type II model. To perform the analyses, we used PLS 3.0 and applied nonparametric bootstrapping (Becker et al., 2012) with 5,000 replications to calculate the standard errors (Becker et al., 2012).

5.1 Measurement model
To estimate the structural model, we start by evaluating the measurement model through reliability and validity analyses. Table 2 reports the descriptive statistics of constructs. The 17 constructs of this study with their relevant abbreviations are summarized. The results show that the mean values of constructs range between 1.835 to 4.397, where risk and insecurity, a measure of technological factor, has the lowest mean while transactional value, a measure of big data analytic adoption, has the highest mean. For each construct, convergent validity and discriminant validity were performed using the Cronbach’s alpha, composite reliability and average variance extracted (AVE). Factor loadings of items were
tested to explore whether each item loads significantly on the constructs. Each item with the loading value of 0.5 was retained for the analysis, as suggested by Efron and Tibshirani (1994). Items with outer loadings below 0.5 were removed. In the initial model, shown in Table 3, three measurement items showed loadings of less than 0.5, thus, they were removed from the model. For adequate convergent validity, the AVE value of 0.5 or more verifies that a latent variable can explain at least 50% of the variance of its indicators (Hair et al., 2016). The AVE values in Table 3 suggest that convergent validity exists with the values of more than 0.5 on average. The values of Cronbach’s alpha and composite reliabilities were all greater than 0.787, above the threshold value of 0.70 (Hair et al., 2013), indicating that the constructs have satisfactory reliability.

A common method bias could be a potential problem (Chin, 1998). Hence we carried Harman’s one-factor test. The untabulated results reveal that the first factor captured only 37.54% of the total variance, below the threshold of 50%, as suggested by Hair et al. (2011), indicating that the common method bias would not be an issue in this research. Additionally, the untabulated results of the correlation matrix indicate that the highest inter-construct correlation obtained using the heterotrait–monotrait ratio of correlations is below 0.90, and the results of Fornell-Larcker criteria show that the square root of average variance extraction is higher than the inter-construct correlations. The results assert that there is no violation of discriminant validity, and it is less likely that there is a common method bias since an extremely high correlation of 0.90 and above does not exist between constructs.

5.2 Structural model
The results of $R^2$ are reported in Table 4 to determine the accuracy of the predictions. The $R^2$ values of BDA adoption, financial performance and market performance are 0.694, 0.680 and 0.582, respectively. These results verify that explanatory variables explain more than 50% of variances. The structural model results are depicted in Table 4. The results show that environmental context ($\beta = 0.235, p < 0.01$), organizational context ($\beta = 0.320, p < 0.001$)

<table>
<thead>
<tr>
<th>Construct</th>
<th>Abbreviation</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strategic value</td>
<td>BDA.SV</td>
<td>4.363</td>
<td>0.606</td>
</tr>
<tr>
<td>Transactional value</td>
<td>BDA.TV</td>
<td>4.397</td>
<td>0.517</td>
</tr>
<tr>
<td>Transformational value</td>
<td>BDA.TR</td>
<td>3.763</td>
<td>0.657</td>
</tr>
<tr>
<td>Informational value</td>
<td>BDA.IV</td>
<td>3.890</td>
<td>0.834</td>
</tr>
<tr>
<td>Relative advantage</td>
<td>TC.RA</td>
<td>4.000</td>
<td>0.561</td>
</tr>
<tr>
<td>Compatibility</td>
<td>TC.CMP</td>
<td>3.964</td>
<td>0.694</td>
</tr>
<tr>
<td>Complexity</td>
<td>TC.CPX</td>
<td>2.244</td>
<td>0.755</td>
</tr>
<tr>
<td>Risk and insecurity</td>
<td>TC.US</td>
<td>1.835</td>
<td>0.741</td>
</tr>
<tr>
<td>Trialability</td>
<td>TC.TR</td>
<td>3.955</td>
<td>0.767</td>
</tr>
<tr>
<td>Observability</td>
<td>TC.OBS</td>
<td>3.855</td>
<td>0.815</td>
</tr>
<tr>
<td>Top management support</td>
<td>OC.TM</td>
<td>3.817</td>
<td>0.712</td>
</tr>
<tr>
<td>Organizational readiness</td>
<td>OC.OR</td>
<td>3.989</td>
<td>0.742</td>
</tr>
<tr>
<td>Competitive pressure</td>
<td>EF.CP</td>
<td>4.024</td>
<td>0.731</td>
</tr>
<tr>
<td>External support</td>
<td>EF.ES</td>
<td>4.104</td>
<td>0.842</td>
</tr>
<tr>
<td>Government regulation</td>
<td>EF.GR</td>
<td>3.936</td>
<td>0.821</td>
</tr>
<tr>
<td>Market performance</td>
<td>MP</td>
<td>3.775</td>
<td>0.705</td>
</tr>
<tr>
<td>Financial performance</td>
<td>FP</td>
<td>3.868</td>
<td>0.847</td>
</tr>
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</table>

Table 2. Descriptive statistics of constructs

Note: BDA = Big Data Analytics, TC = Technological Context, OC = Organizational Context, EC = Environmental context
<table>
<thead>
<tr>
<th>Construct</th>
<th>Item</th>
<th>Initial loading</th>
<th>Modified loading</th>
<th>Cronbach’s α</th>
<th>Composite reliability</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Informational value</td>
<td>BDA.IV1</td>
<td>0.894</td>
<td>0.884</td>
<td>0.886</td>
<td>0.930</td>
<td>0.815</td>
</tr>
<tr>
<td></td>
<td>BDA.IV2</td>
<td>0.931</td>
<td>0.931</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>BDA.IV3</td>
<td>0.883</td>
<td>0.883</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Strategic value</td>
<td>BDA.SV1</td>
<td>0.814</td>
<td>0.814</td>
<td>0.808</td>
<td>0.887</td>
<td>0.723</td>
</tr>
<tr>
<td></td>
<td>BDA.SV2</td>
<td>0.838</td>
<td>0.838</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>BDA.SV3</td>
<td>0.897</td>
<td>0.897</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transformational value</td>
<td>BDA.TRF1</td>
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<td>0.765</td>
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<td>BDA.TRF2</td>
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<td>0.699</td>
<td>0.787</td>
<td>0.860</td>
<td>0.608</td>
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<td></td>
<td>BDA.TRF3</td>
<td>0.795</td>
<td>0.795</td>
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<td>BDA.TRF4</td>
<td>0.850</td>
<td>0.851</td>
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<tr>
<td>Transactional value</td>
<td>BDA.TV1</td>
<td>0.846</td>
<td>0.857</td>
<td>0.855</td>
<td>0.912</td>
<td>0.776</td>
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<td></td>
<td>BDA.TV2</td>
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<td></td>
<td>BDA.TV3</td>
<td>0.921</td>
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<td></td>
<td>BDA.TV4</td>
<td>0.856</td>
<td>0.852</td>
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<tr>
<td>Competitive pressure</td>
<td>EF.CP1</td>
<td>0.874</td>
<td>0.874</td>
<td>0.841</td>
<td>0.904</td>
<td>0.758</td>
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<td></td>
<td>EF.CP2</td>
<td>0.878</td>
<td>0.878</td>
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<tr>
<td></td>
<td>EF.CP3</td>
<td>0.860</td>
<td>0.860</td>
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<td></td>
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<tr>
<td>Government regulation</td>
<td>EF.GR1</td>
<td>0.890</td>
<td>0.880</td>
<td>0.865</td>
<td>0.917</td>
<td>0.787</td>
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<tr>
<td></td>
<td>EF.GR2</td>
<td>0.878</td>
<td>0.878</td>
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<tr>
<td></td>
<td>EF.GR3</td>
<td>0.894</td>
<td>0.894</td>
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<tr>
<td>External support</td>
<td>EF.ES1</td>
<td>0.903</td>
<td>0.903</td>
<td>0.909</td>
<td>0.943</td>
<td>0.846</td>
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<td>EF.ES2</td>
<td>0.936</td>
<td>0.936</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>EF.ES3</td>
<td>0.921</td>
<td>0.921</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organizational readiness</td>
<td>OC.OR1</td>
<td>0.792</td>
<td>0.792</td>
<td>0.886</td>
<td>0.922</td>
<td>0.747</td>
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</tr>
<tr>
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<td>OC.OR3</td>
<td>0.901</td>
<td>0.901</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>OC.OR4</td>
<td>0.862</td>
<td>0.862</td>
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<td></td>
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</tr>
<tr>
<td>Top management support</td>
<td>OC.TM1</td>
<td>0.827</td>
<td>0.827</td>
<td>0.862</td>
<td>0.906</td>
<td>0.708</td>
</tr>
<tr>
<td></td>
<td>OC.TM2</td>
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<td>0.838</td>
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</tr>
<tr>
<td></td>
<td>OC.TM3</td>
<td>0.870</td>
<td>0.870</td>
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<tr>
<td></td>
<td>OC.TM4</td>
<td>0.829</td>
<td>0.829</td>
<td></td>
<td></td>
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<tr>
<td>Compatibility</td>
<td>TC.CMP1</td>
<td>0.882</td>
<td>0.883</td>
<td>0.796</td>
<td>0.880</td>
<td>0.709</td>
</tr>
<tr>
<td></td>
<td>TC.CMP2</td>
<td>0.795</td>
<td>0.793</td>
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<td></td>
<td>TC.CMP3</td>
<td>0.847</td>
<td>0.848</td>
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<tr>
<td>Complexity</td>
<td>TC.CPX1</td>
<td>0.839</td>
<td>0.840</td>
<td>0.794</td>
<td>0.878</td>
<td>0.706</td>
</tr>
<tr>
<td></td>
<td>TC.CPX2</td>
<td>0.863</td>
<td>0.863</td>
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<td></td>
<td>TC.CPX3</td>
<td>0.818</td>
<td>0.819</td>
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<tr>
<td>Observability</td>
<td>TC.OBS1</td>
<td>0.797</td>
<td>0.797</td>
<td>0.918</td>
<td>0.939</td>
<td>0.755</td>
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<td></td>
<td>TC.OBS2</td>
<td>0.880</td>
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<td></td>
<td>TC.OBS3</td>
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</tr>
<tr>
<td></td>
<td>TC.OBS4</td>
<td>0.889</td>
<td>0.888</td>
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<tr>
<td></td>
<td>TC.OBS5</td>
<td>0.874</td>
<td>0.873</td>
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<tr>
<td>Relative advantage</td>
<td>TC.RA1</td>
<td>0.781</td>
<td>0.813</td>
<td>0.858</td>
<td>0.903</td>
<td>0.700</td>
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<td></td>
<td>TC.RA2</td>
<td>0.832</td>
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<td>TC.RA3</td>
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<td>TC.RA5</td>
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<td>0.848</td>
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<td>TC.RA6</td>
<td>0.379</td>
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</table>

Table 3. The results of convergent validity (continued)
and technological context ($\beta = 0.377, p < 0.001$) have significant positive effects on big data analytics adoption. TOE contextual variables significantly increase the adoption of big data analytic among SMEs, and thus, $H1$, $H2$, and $H3$ are supported. Additionally, big data analytics adoption significantly positively affects financial and market performance ($\beta = 0.392, p < 0.001$, and $\beta = 0.321, p < 0.05$, respectively). As such, $H4$ and $H5$ are supported. The direct effects of IV and DV are also reported in Table 5. The results show that environmental and organizational contexts influence financial performance, and technological context affects market performance. Table 6 reports the indirect effects between IV and DV.

The results reveal that big data analytics adoption significantly mediates the relationships of organizational and technological context variables and financial and market performance. While big data analytics adoption mediates environmental context and financial performance, it does not have any effect on the relationship between environmental context and market performance. Full mediation effects are observed between environmental context and market performance ($\beta = 0.103, p < 0.05$), and technological context and financial performance ($\beta = 0.148, p < 0.01$). Hence, hypotheses $H6$, $H8$, $H9$, $H10$ and $H11$ are supported while $H7$ is rejected.
6. Discussion
While the growth of BDA technology is continuously increasing, the conditions under which such technology ends up with business value creation for SMEs remain fundamentally ambiguous in empirical research. The majority of the publications in the context of SMEs have focused on different technology adoption, and rarely the technology of BDA is covered, while BDA could be effective to adopt if industries would be able to increase the capability of their BDA investment. Therefore, SMEs are left behind as compared to large companies, while they are the main contributors to economic growth and need to upgrade their business environment by adopting modern organizational innovation. However, only a small number of companies, even large organizations, have been successful in gaining the full potential of BDA adoption in their businesses (Mikalef et al., 2019).

The main objective of this study is to explore what factors, in terms of technology, organization and environment, may affect the adoption of BDA among SMEs and whether BDA enables SMEs to enhance their performance. SMEs’ issues in adopting e-commerce have been due to skills shortages, weak management practices and inadequate training for human

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Relationship</th>
<th>Path coefficients</th>
<th>Decision</th>
</tr>
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<tbody>
<tr>
<td><em>Path a</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H1</td>
<td>EC → BDA</td>
<td>0.235**</td>
<td>Supported</td>
</tr>
<tr>
<td>H2</td>
<td>OC → BDA</td>
<td>0.320***</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>TC → BDA</td>
<td>0.377***</td>
<td>Supported</td>
</tr>
<tr>
<td><em>Path b</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H4</td>
<td>BDA → FP</td>
<td>0.392***</td>
<td>Supported</td>
</tr>
<tr>
<td>H5</td>
<td>BDA → MP</td>
<td>0.321*</td>
<td>Supported</td>
</tr>
<tr>
<td><em>Path c’</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>–</td>
<td>EC → FP</td>
<td>0.248**</td>
<td>–</td>
</tr>
<tr>
<td>–</td>
<td>EC → MP</td>
<td>0.127</td>
<td>–</td>
</tr>
<tr>
<td>–</td>
<td>OC → FP</td>
<td>0.228*</td>
<td>–</td>
</tr>
<tr>
<td>–</td>
<td>OC → MP</td>
<td>-0.004</td>
<td>–</td>
</tr>
<tr>
<td>–</td>
<td>TC → FP</td>
<td>0.051</td>
<td>–</td>
</tr>
<tr>
<td>–</td>
<td>TC → MP</td>
<td>0.387***</td>
<td>–</td>
</tr>
</tbody>
</table>

Notes: *p < 0.05; **p < 0.01; ***p < 0.001; BDA = Big Data Analytics, TC = Technological Context, OC = Organizational Context, EC = Environmental Context, FP = Financial Performance, MP = Market Performance

Table 5. Path coefficients and hypothesis testing

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Relationship</th>
<th>Path coefficients</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>H6</td>
<td>EC → BDA → FP</td>
<td>0.092*</td>
<td>Supported</td>
</tr>
<tr>
<td>H7</td>
<td>EC → BDA → MP</td>
<td>0.076</td>
<td>Not supported</td>
</tr>
<tr>
<td>H8</td>
<td>OC → BDA → FP</td>
<td>0.126**</td>
<td>Supported</td>
</tr>
<tr>
<td>H9</td>
<td>OC → BDA → MP</td>
<td>0.103*</td>
<td>Supported</td>
</tr>
<tr>
<td>H10</td>
<td>TC → BDA → FP</td>
<td>0.148**</td>
<td>Supported</td>
</tr>
<tr>
<td>H11</td>
<td>TC → BDA → MP</td>
<td>0.121*</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Notes: *p < 0.05; **p < 0.01; ***p < 0.001; BDA = Big Data Analytics, TC = Technological Context, OC = Organizational Context, EC = Environmental Context, FP = Financial Performance, MP = Market Performance

Table 6. Indirect effect
resources and financial barriers in Iran (Ghobakhloo et al., 2011b). Arasti et al. (2014) suggested that SMEs in Iran need much higher infrastructural and financial support to benefit from IT and developing their capabilities to contribute to economic development. Further studies show that the main issues for ICT adoption among Iranian SMEs are lack of environmental support (Akbari and Alipour Pijani, 2013; Tatī, 2011). In this sense, the current study explored how TOE contextual variables affect SMEs’ decision to adopt new emerging technology such as BDA in Iran and how BDA influence their performance. This study statically found that the adoption of BDA depends on three primary contexts, which are technology, organization and environment. The result of the current research is compatible with the previous study by Ramdani et al. (2013) showing that technological, organizational and environmental contexts could impact the adoption of enterprises applications among SMEs.

The result of this study indicated that the business value originated from BDA improves the performance of SMEs in Iran. However, only the EC → BDA → MP with a path coefficient of 0.076 was not supported. More precisely, this study claims that technological and organizational elements are more significant variables that would help SMEs to gain business value from the adoption of BDA and increase their performance. The findings of this research are considerably distinguishable from the current literature in the area of BDA and its business value. Our results show that all the factors studied in this study such as relative advantage, compatibility, complexity, risk and insecurity, trialability, observability, top management support, organizational readiness, competitive pressure, external support and government regulation must be emphasized in manufacturing sector of SMEs to have a successful usage of BDA in their businesses.

The researchers assert that BDA does not require a large organization to make an effect. The realm of BDA is no longer limited to larger companies. Smaller firms can experience digital transformations and create capabilities for the use of vast scale data analytics. There should be an opportunity for SMEs to overcome the challenges faced across the industry for making business values of BDA. To gain business value from BDA, SMEs do not need to provide their businesses with technical skills. SMEs have the opportunity of taking advantage of BDA by the outsourcing of some resources like technical skills. However, the role of government and top managements’ support for the initiation of BDA is undeniable.

Effective use of BDA can be considered as a capability for SMEs to encourage them to adopt it in different sectors and industries. What makes the adoption of BDA notable among SMEs is that they need to know how to deal with technological, organizational and environmental aspects to using the business values of BDA. Many scholars have already started to imply the significance of all these elements in order to mature their BDA capabilities (Mikalef et al., 2019). However, among SMEs, the factors might be different, which the majority of the current literature has not distinguished them. Finally, the findings of this study suggest that SMEs should consider BDA as a significant strategy to make sure that they can improve the performance of their firms. As such, SMEs need to consider the factors that may influence the adoption of such a strategy. However, they must be aware that some differences may arise, depending on the specific sectors in which they want to invest (Raguseo and Vitari, 2018).

6.1 Theoretical and practical implications

The current study would be useful for decision-makers within the manufacturing sector and scholars, as it is substantial evidence on the TOE drivers of BDA adoption and their relationship with SMEs’ performance. As one of the main theoretical implications, the unified model of BDA for SMEs, allows the Iranian SMEs to gain knowledge about BDA adoption. Grounding in RBV theory, this study attempted to examine the mediating role of
BDA adoption between TOE variables and SMEs’ performance. While drawing on the RBV of the firm, the current study considered TOE contexts as intangible capabilities of SMEs decision-makers, which could directly influence the performance of firms. Besides, BDA adoption itself can be regarded as a knowledge capability and resource for SMEs to improve their performance. Narwane et al. (2020) very recently found that cloud of things would be a mediator for SMEs to improve their performance. In Narwane et al.’s (2020) study, the determinants are similar to the TOE factors, although the these scholars did not categorize the factors within s TOE framework.

The findings also offer a guideline for policymakers in developing countries. Most of the developed countries have already initiated applicable programs for technology adoption, and developing countries must follow suit. Therefore, they need more studies, guidelines and models to assist SMEs to take advantage of new technologies. Decision-makers of SMEs need to enhance their understanding and knowledge about the effective adoption of BDA in the manufacturing environment. Previous studies indicated that organizations that could increase their BDA capabilities, in particular technological and organizational ones, have been more capable to boost up their performance consequently (Mikalef et al., 2019).

Further, organizations need to improve their data-driven culture to increase their ability to have a successful digital transformation (Rialti et al., 2018a; Rialti et al., 2018b). The current study also supports the notion that practitioners must first initiate a coherent and unambiguous data-driven culture and infrastructure if they aim to benefit from BDA. As such, SMEs would be able to build and maintain a resilient data-driven culture if they attempt to change the mindset of employees toward a data-driven mindset. Therefore, they capitalize on the adoption of BDA in their businesses. Besides, SMEs are different from large companies in terms of availability of resources and support. Thus, it highlights the role of service providers and external support from the government and partners.

According to Narwane et al. (2020), developing countries face critical challenges such as inadequate IT resources, weak communication and an insufficient pool of experts. As such, the role of external supports and also internal support from the CEOs and their representatives would be vital to creating a digital environment and adopting new technologies. SMEs can make proper and logical decisions and use the opportunities to receive assistance from vendors and the government to invest more in using modern digital technologies. Governments also need to create conducive environments and adequate enforcements for SMEs for the adoption of new and advanced technologies. Due to economic instability and sanctions imposed on Iran, policymakers need to pay more attention to SMEs and provide adequate support. Training, educational programs and financial assistance might be appropriate ways to increase the confidence of SMEs that they would be able to catch the benefits BDA. That is because of the common belief that exists among Iranians that a supportive environment can increase entrepreneurial traits of SMEs in Iran and, therefore, encourage them to take more entrepreneurial actions, for example, embracing newly emerged technologies for further development (Emami and Khajeheian, 2019).

7. Conclusion and future directions

In this study, the direct relationship between TOE contexts and BDA adoption, and BDA adoption and firm performance (financial and market) were investigated among Iranian SMEs. Additionally, the indirect effects of TOE contexts and firm performance through BDA adoption were explored. The findings reveal that TOE contexts have significant positive effects on BDA adoption, and BDA adoption further improves the performance of SMEs. The empirical results show that the adoption of BDA in SMEs mediates the impacts of TOE contexts on financial performance. Concerning market performance, BDA adoption
only mediates the effects of organizational and technological contexts on market performance. Full mediations were observed in the relationship between organizational context and market performance and technological context and financial performance, where the direct effects of these relationships were insignificant. The environmental context does not have any relationship with market performance in both direct and indirect estimations.

While the aim of this study is deemed to be achieved, the limitations should delineate the future directions. First, this study approached only one key informant in each SME, that is, the owner, CEO, or senior executive. The present study did not seek information from employees who are involved in BDA in the firms. Future studies may collect data from at least two informants per SMEs, one from the top-level managers and one from the employees. Furthermore, this study investigates the context of Iranian manufacturing SMEs, and therefore the findings could not be generalized to other countries and sectors. Future researchers may proceed with a similar approach in other developing countries and different industries and sectors. According to Emami and Khajeheian (2019) and Javidan and Dastmalchian (2003), due to close historical ties that exist between Iran and some South Asian as India, Indonesia, the Philippines, Malaysia and Thailand, future studies can replicate this research model among countries above. It may also help to validate the finding of the current study.

Future scholars may consider different determinants or technological, organizational and environmental factors as the TOE model is flexible. By doing so, researchers can include and exclude the elements that are compatible with the context of their studies and, therefore, it may deliver different results. Finally, the present empirical study used a quantitative method of research in which the answers given by respondents were limited to the alternatives provided in the survey. Hence, future researchers can provide more reliable findings through a focus group and observation or qualitative methodology.

References


OECD (2017), “Enhancing the contributions of SMEs in a global and digitalised economy”, *Meeting of the OECD Council at Ministerial Level*.


Appendix

Big data analytics adoption

Strategic value (Raguseo and Vitari, 2018)
My company has used big data analytics to:
- respond more quickly to change;
- create competitive advantage; and
- improve customer relations.

Transactional value (Raguseo and Vitari, 2018)
My company has used big data analytics to:
- enhance savings in supply chain management;
- reduce operating costs;
- reduce communication costs; and
- enhance employee productivity.

Transformational value (Raguseo and Vitari, 2018)
My company has used big data analytics to:
- improve employees’ skill level;
- develop new business opportunities;
- expand capabilities; and
- improve organizational structure and processes.

Informational value (Raguseo and Vitari, 2018)
My company has used big data analytics to:
- enable faster access to data;
- improve management data; and
- improve data accuracy.

Technological context

Relative advantage (Chen et al., 2015; Ghobakhloo et al., 2011a; Premkumar and Roberts, 1999)
- Big data analytics improves the quality of work.
- Big data analytics makes work more efficient.
- Big data analytics lowers costs.
- Big data analytics improves customer service.
- Big data analytics attracts new sales to new customers or new markets.
- Big data analytics adoption identifies new product/service opportunities.

Compatibility (Chen et al., 2015; Ghobakhloo et al., 2011a; Thong, 1999; Tornatzky and Klein, 1982)
- Using big data analytics is consistent with our business practices.
- Using big data analytics fits our organizational culture.
- Overall, it is easy to incorporate big data analytics into our organization.

Complexity (Lai et al., 2018; Xu et al., 2017)
- Learning to use the big data analytics is difficult for employees.
- Big data analytics is difficult to maintain.
- Big data analytics is difficult to operate.
Trialability (Elsebeth, 2013; Limthongchai and Speece, 2003; Moore and Benbasat, 1991)

- My company could access to a free trial before making a decision to adopt big data analytics.
- My company has the opportunity to try a number of big data analytics applications before making a decision and try out big data analytics software packages on a sufficiently large scale.
- My company is allowed to use big data analytics on a trial basis long enough to see its true capabilities.
- It is easy to get out after testing a big data analytics package.
- The start-up cost for using big data analytics is low.

Risk and insecurity (Salleh and Janczewski, 2016; Shin and Shin, 2011)

- The need to outsource big data analytics creates concerns on data security and privacy.
- The need to outsource big data analytics creates vulnerability in access control of the organization’s information asset.
- The need to outsource big data analytics creates risks through excessive dependency towards vendor.
- The need to outsource big data analytics complicates the process of implementing corporate policy in protecting individual privacy and data security.

Observability (Limthongchai and Speece, 2003; Moore and Benbasat, 1991)

- Many competitors or business partners in the market have started using big data analytics.
- Using big data analytics helps my company to connect with both domestic and international business partners.
- There are many computers that people in the company can access to use big data analytics.
- Big data analytics shows improved results over doing business the traditional way.

Organizational context

Top management support (Chen et al., 2015; Lai et al., 2018; Priyadarshinee et al., 2017)

- Our top management promotes the use of big data analytics in the organization.
- Our top management creates support for big data analytics initiatives within the organization.
- Our top management promotes big data analytics as a strategic priority within the organization.
- Our top management is interested in the news about using big data analytics adoption.

Organizational readiness (Chen et al., 2015)

- Lacking capital/financial resources has prevented my company from fully exploit big data analytics.
- Lacking needed IT infrastructure has prevented my company from exploiting big data analytics.
- Lacking analytics capability prevent the business fully exploit big data analytics.
- Lacking skilled resources prevent the business fully exploit big data analytics.
Environmental context

**Competitive pressure** *(Lai et al., 2018)*

- Our choice to adopt big data analytics would be strongly influenced by what competitors in the industry are doing.
- Our firm is under pressure from competitors to adopt big data analytics.
- Our firm would adopt big data analytics in response to what competitors are doing.

**External support** *(Ghobakhloo et al., 2011a; Ghobakhloo et al., 2011b; Li, 2008)*

- Community agencies/vendors can provide required training for big data analytics adoption.
- Community agencies/vendors can provide effective technical support for big data analytics adoption.
- Vendors actively market big data analytics adoption.

**Government regulation** *(Agrawal, 2015; Gupta and Barua, 2016; Lai et al., 2018; Li, 2008)*

- The governmental policies encourage us to adopt new information technology (e.g., big data analytics).
- The government provides incentives for using big data analytics in government procurements and contracts such as offering technical support, training and funding for big data analytics use.
- There are some business laws to deal with the security and privacy concerns over the big data analytics technology.

**Firm performance**

**Firm market performance** *(Ren et al., 2017; Raguseo and Vitari, 2018)*

Compared with your major competitors, how do you rate your firm’s performance in the following areas over the past 3 years:

- entering new markets quickly;
- introducing new products or services to the market quickly;
- success rate of new products or services; and
- market share.

**Firm financial performance**

Compared with your major competitors, how do you rate your firm’s performance in the following areas over the past 3 years:

- improving customer retention;
- improving sale growths; and
- improving profitability.

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