Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations

Abstract

The importance of big data analytics, artificial intelligence, and machine learning has been at the forefront of research for operations and supply chain management. Literature has reported the influence of big data analytics for improved operational performance, but there has been a paucity of research regarding the role of entrepreneurial orientation (EO) on the adoption of big data analytics. To address this gap, we draw on the dynamic capabilities view of firms and on contingency theory to develop and test a model that describes the role of EO on the adoption of big data analytics powered by artificial intelligence (BDA-AI) and operational performance (OP). We tested our research hypotheses using a survey of 256 responses gathered using a pre-tested questionnaire from manufacturing firms in India with the help of the National Association of Software and Services Companies (NASSCOM) and the Federation of Indian Chambers of Commerce and Industry (FICCI). The results from our analysis of data indicate that EO is an important characteristics of an organisation that enable the organisation to exploit and further explore the BDA-AI capabilities to achieve superior OP. Further, our results provide an empirical evidence based on data that EO are more associated with higher order capabilities (such as BDA-AI) and OP under differential effects of ED. These findings extend dynamic capability view and contingency theory to create better understanding of dynamic capabilities of the organisation while also providing theoretically grounded guidance to the managers to align their EO with their technological capabilities within their firms.

Keywords: Big Data Analytics, Artificial Intelligence, Entrepreneurial Orientation, Operational Performance, Supply Chain Management, PLS SEM.

1. Introduction

Data has become one of the most valuable assets for modern organisations (Weerakkody et al., 2017; Kozjek et al., 2018; Albergaria and Jabbour, 2019). Moreover, organisations are becoming increasingly digital, and as a result a large volume of data is being generated in their supply chains (Sheng et al., 2017; Tan et al., 2017; Akter et al., 2017; Ji-Fan Ren et al., 2017; Ivanov et al., 2019a; Frank et al., 2019; Dolgui et al., 2019a,b). However, unlike capital, big data has no value without the tools by which deeper insights can be extracted from it (Chen et al., 2012; Waller and Fawcett, 2013; Gandomi and Haider, 2015; Aydiner et al., 2019). The best-informed managers with the greatest understanding of their data (Hazen et al., 2014; Hazen et al. 2017; Verma and Bhattacharyya, 2017; Cao and Duan, 2017; Kache and Seuring, 2017) can use it to create benchmarks for their organisation (Merendino et al., 2018; Mikalef et al., 2019a; Chehbi-Gamoura et al. 2019). Big data and predictive analytics helps organisations *reduce costs* (Choi et al. 2018; Aydiner et al., 2019; Dubey et al., 2019), *make products faster* (Giannakis and Louis, 2016; Dubey et al., 2018), and *create new products or services* to meet customers' changing needs (George et al., 2014; Opresnik and Taisch, 2015; Choi et al. 2018; Ghasemaghaei and Calic, 2019). The future of supply chain digitization will be driven by big data predictive analytics capability, powered by artificial intelligence (O'Leary, 2013; Loebbecke and Picot, 2015; Zhong et al., 2016; Kusiak, 2018; Ivanov et al., 2016, 2019b; Baryannis et al., 2019; Tortorella et al. 2020). Hence, the applications in the management field of big data analytics (BDA), machine learning (ML), and artificial intelligence (AI) have received increased attention (Waller and Fawcett, 2013; Chen and Zhang, 2014; Sivarajah et al., 2017; Delen and Zolbanin, 2018; Cavalcante et al., 2019; Dwivedi et al. 2019); with businesses increasingly investing in emerging technologies related to these applications in order to gain competitive advantage (Dalenogare et al. 2018; Aydiner et al., 2019; Dubey et al., 2019).

In response to high customer expectations, intense global competition, and a rapidly changing technological landscape, organisations must raise their entrepreneurial profile if they want to gain competitive advantage (George and Marino, 2011; Dwivedi et al., 2011; Boso et al., 2013; Chavez et al., 2017; Arunachalam et al., 2018; Sahi et al., 2019 a,b; Cenamor et al., 2019). Moreover, developing economies are rapidly moving to market-based policies to enhance economic growth and reduce poverty (Boso et al., 2013). In doing so, organisations operating in such economies are facing rapid structural changes, increased environmental uncertainty, and unbalanced growth (Ivanov and Sokolov, 2013). Ivanov and Sokolov (2012,

p. 6133) further state that, '*supply chains are multi-structural semantics and often have interrelated structures (i.e., organisational, functional, informational, financial, topological, technological, product and energy structures) are dynamic and subject to many planned and disturbance-based changes'*. Hence, we argue that these current dynamics have shaped the managerial assumptions and decision-making processes of many organisations. Hughes (2018) suggests that despite the excitement generated by the potential of big data analytics powered by artificial intelligence (BDA-AI) amongst organisations and academia, organisations from developing economies remain sceptical about its application and potential benefits. Major factors that may account for such scepticism include lack of top management commitment, under-estimating competition, ignoring customers' immediate needs, lack of differentiation, and ineffective marketing (Shah et al., 2017; Dubey et al., 2019; Duan et al., 2019; Akhtar et al., 2019).

The literature on the performance benefits of entrepreneurial organisations has received significant attention from organisational researchers (Rauch et al., 2009; Boso et al., 2013; Rosenbusch et al., 2013; Arunachalam et al., 2018; Sahi et al., 2019 a,b). Scholars argue that technological innovation is not only the key success factor in global competitive markets but also plays an important role in the operations of an enterprise (see Lin et al., 2016; Zhai et al., 2018; Ivanov et al., 2018). They have increasingly studied the role of emerging technologies (i.e., big data analytics/big data predictive analytics) on operational performance (OP) (Akter et al., 2016; Gupta and George, 2016; Fosso Wamba et al., 2017; Mikalef and Pateli, 2017; Golzer and Fritzsche, 2017; Srinivasan and Swink, 2018; Dubey et al., 2019; Aydiner et al., 2019; Mikalef et al., 2019b) and BDA-AI (Duan et al., 2019; Abubakar et al., 2019; Gursoy et al., 2019).

Although an extensive body of emerging technologies adoption literature exists, studies on the role of entrepreneurial orientation (EO) on the adoption of emerging technologies (i.e., BDA/BDA-AI) remain relatively scarce, despite the importance of understanding this phenomenon (Levesque and Joglekar, 2018; Canakoglu et al., 2018; Duan et al., 2019). Furthermore, the limited number of studies on organisations adopting emerging technologies that do exist generally focus on understanding the direct impact on operational performance (see Akter et al., 2016; Fosso Wamba et al., 2017) or on the indirect impact (Aydiner et al., 2019). These studies do not go deeper in trying to understand the impact of entrepreneurial orientation on the adoption of emerging technologies and OP. In order to take action, it is necessary to understand the effect of the factors that have a bearing on the situation. Hence, to enhance understanding of the interplay between EO, BDA-AI and OP, we generate our first research question:

RQ1: *What are the distinct and joint effects of EO and BDA-AI on operational performance?*

Management scholars have previously argued that the direct effects are crucial, but they seem incapable of explaining the complexity of real-world phenomena (Boyd et al., 2012; Eckstein et al., 2015). This view is reflected in contingency theory (CT) (see Lawrence and Lorsch, 1967). The conceptual and empirical research on EO and BDA-AI has largely neglected the influence of contextual factors, so, in this study, we use the theoretical lens of CT to understand the conditions under which EO and BDA-AI are highly effective.

Environmental dynamism (ED) has been recognised as a key situational element in dynamic capabilities theory (Eisenhardt and Martin, 2000), which suggests that the variance of operational performance created by organisational capability is contingent on environmental dynamism (Chen et al., 2015). Chen et al. (2015) established the moderating effects of ED on the path joining BDA use and asset productivity/business growth and, in a similar fashion, ED may have an effect on the paths EO-BDA-AI/OP. However, such effects have not been subjected to empirical testing. Hence, we specify our second research question:

RQ2: *What are the effects of ED on the paths joining EO and BDA-AI/OP?*

We answer our research questions by analysing data collected from a sample of 256 manufacturing organisations, using factor-based PLS-SEM. To theoretically corroborate our empirical results, we integrated *dynamic capability view (DCV)* (e.g. Teece et al., 1997; Eisenhardt and Martin, 2000) and *contingency theory (CT)* (e.g. Donaldson, 2001), because neither perspective can, on its own, explain both the direct effect of EO on BDA-AI and OP and the situations under which the effects of EO on BDA-AI and OP are effective.

We have organised our paper as follows. In the second section, we provide the theoretical foundations and research hypotheses of our study. In Section 3, we present our research design, which includes discussion of the operationalisation of the constructs, the sampling design, the data collection process, and the non-response bias test. In Section 4, we discuss our study data analysis and the results. In Section 5, we discuss implications for theory and practice, the limitations of our study, and future research directions. Finally, we draw some conclusions.

2. Underpinning theories and hypotheses development

Having understood that the existing literature on the implementation of emerging technologies offers only a limited understanding of the indirect and impacts of the technologies on operational performance (OP), and bearing in mind that managers considering taking action need to understand the likely effects of their actions, our motivation is to look at the theories that can be applied to inform our study.

Our theoretical model is founded on two elements: entrepreneurial orientation (EO) and dynamic capabilities view (DCV). In organisational literature EO has gained significant attention in the last three decades (Farkas, 2016). Informed by recent arguments (see, Woldesenbet et al. 2012) we argue that role of EO abilities and dynamic capabilities are critical for operating effectively in volatile, uncertain, complex and ambiguous environments (Sok et al. 2016). Hence, we propose to develop a theoretical model informed by these two theories. In the following sections we discuss the underpinning theories and our proposed theoretical model.

2.1 Entrepreneurial orientation (EO)

EO refers to organisations' tendency to explore new market opportunities (Boso et al., 2013) via building capabilities including innovativeness, risk taking, pro-activeness, competitive aggressiveness, and autonomy (Lumpkin and Dess, 1996). EO emanates from top management; it must be taken seriously throughout the organisation and EO initiatives must be supported by the allocation of adequate resources (Engelen et al., 2015; Arunachalam et al., 2018). It reflects an opportunity-seeking orientation involving a process of exploring new market opportunities that may offer benefits to the organisation (Wiklund and Shepherd, 2011; Boso et al., 2013). Baker and Sinkula (2009) argue that organisations that are highly entrepreneurially-oriented are the most proficient in creating new organisational forms and industry configurations, through which they can shape market arrangements to their advantage. George and Marino (2011) argue that EO has its roots in the work of Mintzberg (1973) and Khandwalla (1976), who found that entrepreneurial organisations have a higher tendency to take risks in comparison to other organisations and are more proactive in exploring new business opportunities.

Miller (1983) was one of the first attempts to operationalise the EO construct and based on their works we define EO as a multidimensional construct that encompasses an organisation's actions relating to *innovation*, *risk taking*, and *pro-activeness*. We concur with Miller's assertion that a non-entrepreneurial organisation is an organisation "*which innovates very little, is highly risk averse and imitates their competitors instead of leading the way*" (p.771). Merz and Sauber (1995, p.554) further defined EO as "*the firm's degree of pro-activeness (aggressiveness) in its chosen product-market unit and its willingness to innovate and create new offerings*". This definition does not include the risk-taking element. Moreover, the definition applies to actions within individual units of the organisation, as opposed to an overall strategic posture, and it applies only to innovation that results in new offerings. Lumpkin and Dess (1996) extended the Miller (1983) definition by suggesting five dimensions of EO. These five dimensions are: *autonomy*, *innovativeness*, *risk taking*, *pro-activeness*, and *competitive aggressiveness*. Lumpkin and Dess (1996, p.136) add that "*an EO refers to the processes, practices, and decision-making activities that lead to new entry*". Clovin and Slevin's (1991) definition runs somewhat contrary to Lumpkin and Dess', as they suggest that an organisation that takes risks associated with the business and is determined to develop new, innovative solutions for existing markets as a means to gain competitive advantage over their competitors may possess high EO. However, as their business activities may not lead to a new entry, they may not satisfy the definition of EO as per Lumpkin and Dess (1996). Hence, we argue that there was a lack of consistency and clarity in the conceptualisation of EO in the earlier literature. In response to these issues, George and Marino (2011) sought to provide better clarity and our study is particularly informed by this later work. Hence, based on all the previous works, we posit that organisations can influence investment in emerging technologies, such as BDA-AI, if they are entrepreneurially oriented.

2.2 Dynamic capability view (DCV)

Dynamic capability (DC) is defined as the organisational "*ability to integrate, build, and reconfigure internal and external resources/competences to address, and possibly shape, rapidly changing business environments*" (Teece, 2012, p. 1395). DC is also known as higher-order capability (Teece, 2014), and was proposed by Teece et al. (1997) as an extension of the resource-based view (RBV) to explain firms' competitive advantage in volatile markets and highly dynamic, changing environments (Winter, 2003; Teece, 2012; Eckstein et al., 2015). Management literature has extensively focused on the operationalisation of the DC construct. For example, Teece (2014) proposed a conceptualisation of DC with three main dimensions: (1) the "sensing" capability, or the ability of a given organisation to identify, develop, co-develop, and assess technological opportunities that can meet customer needs and business opportunities; (2) the "seizing" capability, or the ability of the organization to mobilize required resources to fulfil identified customer needs and business opportunities, thus capturing the resulting business value; and (3) the "transforming" or "reconfiguring" capability, which encompasses all activities that "*recombine bundles of resources and ordinary capabilities*" (Fainshmidt et al. 2016; p.2) to "*innovate and respond to (or bring about) changes in the market and in the business environment more generally*" (Teece, 2014, p.332). Wilhelm et al.

(2015) also outlined three dimensions of DC i.e. “sensing”, “learning” and “reconfiguring” capabilities. Here, the learning capability plays the role of the seizing capability proposed by Teece (2014). Wilhelm et al. (2015, p.329) defined learning capability as “*the firm ability to develop means and tools to efficiently face environmental changes and opportunities that may arise”*. Such a focus of activities is similar to the seizing capability as proposed by Teece (2014).

All these capabilities are expected to, inter alia: allow firms to identify customer needs and business opportunities (Wu, 2010) whilst at the same time striving to survive and grow by responding to changes in the external environment (Mikalef and Pateli, 2017). A firm does this by adjusting its processes to reduce costs (Wilden et al., 2013), allowing it to innovate profitably (Teece, 2012); offer themselves new sets of decision choices (Wilden et al., 2013); generate new knowledge, processes, and products (Pezeshkan et al., 2016); and determine the best moment and ways to align and realign their core internal and external resources with their strategy (Teece, 2014).

Despite the prevalence of DCV, some scholars have argued that a theory like RBV suffers from context insensitivity (Ling-Yee, 2007; Gunasekaran et al., 2017). Hence, we argue that it is necessary to consider under which conditions resources or capabilities may be most valuable. Contingency theory (CT) addresses this notion of the importance of context in explaining how internal and external conditions lead to different performance outcomes. The next section reviews the theory as it relates to our study.

2.3 Contingency theory (CT)

CT suggests that organisations must adapt depending upon the conditions in which they exist (Donaldson, 2001). A contingent DCV has been suggested by scholars to address some of the limitations of the DCV (see Eckstein et al., 2015). Sirmon and Hitt (2009) argue that contingencies have a significant role in achieving competitive advantage through the bundling of resources and capabilities. The development of this theory is useful to explain how the dynamic capabilities of the organisation may provide value (Aragón -Correa and Sharma, 2003; Schilke, 2014). To further enhance the usefulness of the theory and to identify conditions which affect the utility of these resources or capabilities, Volberda et al. (2012) argue that managers should carefully examine the organisation’s internal and external environment and adapt to the conditions accordingly. Hence, while considering contingency theory, different concepts of fit can be employed and should be explicitly considered when conducting research (Sousa and Voss, 2008). Therefore, based on the work of Schilke (2014), we employ a contingency perspective that is operationalised within a moderation concept of fit, which assumes that the differential effect of EO on BDA-AI and OP relies upon the level of moderating variable ED.

2.4 Theoretical model

We first directly link EO to BDA-AI and OP, examining the role of EO on the adoption of BDA-AI and of enhancing operational performance. Here, adoption of BDA-AI refers to the use of big data analytics powered by artificial intelligence to extract more meaningful information with which organisations can improve their decision-making skills. In this study, we focus on two performance criteria: marketing performance and financial performance as a single construct for OP. Furthermore, we develop hypotheses on the contingent effects of environmental dynamism (ED). Finally, we control for the effects of organisation size (OS) and type of industry (IT). Out theoretical model is shown in Figure 1.

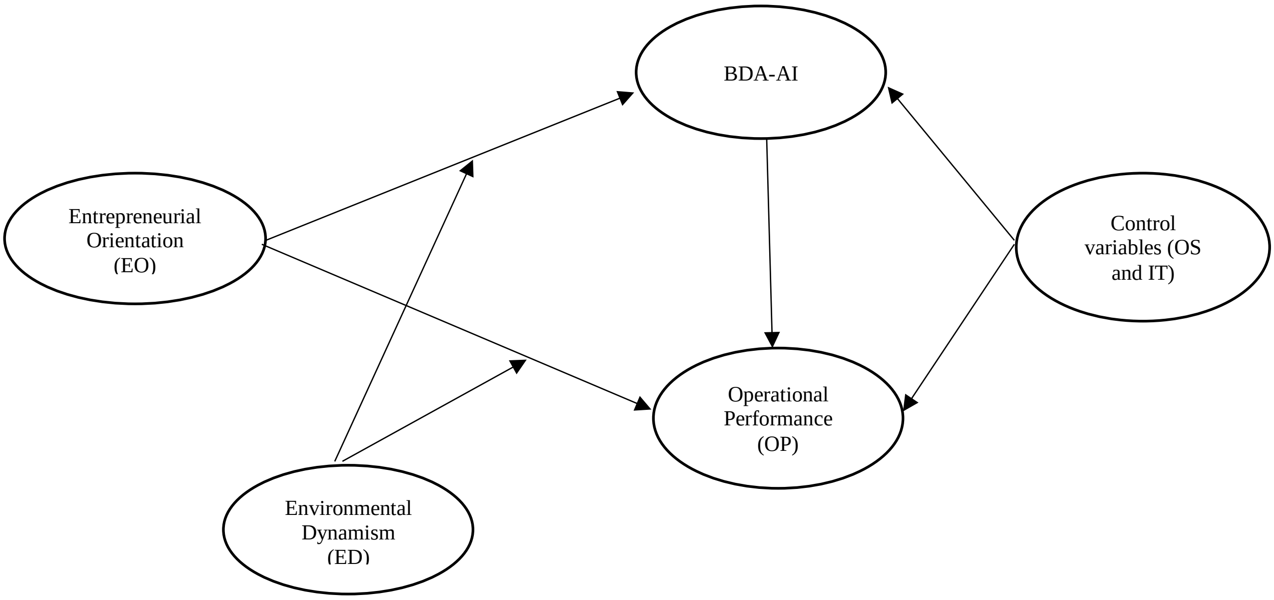

Figure 1: Theoretical model (see text for origin of each concept)

2.4.1 Entrepreneurial orientation (EO) and adoption of big data analytics powered by artificial intelligence (BDA-AI)/operational performance (OP)

In today's dynamic market conditions, competitive advantage rests on the ability to use BDA-AI to better understand customer intentions or behaviours (Duan et al., 2019). Zhai et al. (2018, p.3) argue that EO "*can summarise the performance of style, decision, and the action in the process of the company's business strategy*". The entrepreneurial behaviour demonstrated by the organisation is often echoed in the organisational core philosophy; however, the EO is focused on how organisations do their business (Miller, 1983; George and Marino, 2011). Wu (2007) further argues that entrepreneurial resources are one of the key organisational resources that help organisations respond to dynamic environments. BDA-AI enabled dynamic capabilities are necessary components for gaining significant competitive advantage (Demirkan and Delen, 2013). Moreover, EO includes activities like innovation, exploring new opportunities, and using available resources effectively (Joglekar and Levesque, 2013; Hora and Dutta, 2013; Krishnan, 2013). Hence, we argue that both EO and BDA-AI enabled dynamic capabilities allow organisations to enhance operational performance by creating new products or services, improving product or service quality, reducing cost, and reducing the market risk of new products or services innovation. Wilkund and Shepherd (2005) state that since the innovation process is both costly and risky, organisations need to leverage BDA-AI enabled dynamic capabilities not only to reduce the market risk of new innovations but also to extract enough value from them to cover the high cost of innovation and to provide higher-than-usual profits for the firm (Arunachalam et al., 2018). Following Miller's (1983) arguments, entrepreneurially oriented organisations possess three main characteristics that enable them to strategically navigate through the streams of innovation, new technologies, and new customer trends: innovativeness, pro-activeness, and risk taking. Hence, we posit that these qualities of entrepreneurially oriented organisations can directly influence the organisations' decisions to invest in creating organisational resources that help create BDA-AI capability. Hence, we hypothesise:

H1: EO has a significant positive effect on adoption of BDA-AI; and

H2: EO has a significant positive effect on OP.

2.4.2 Big data analytics powered by artificial intelligence (BDA-AI) and operational performance (OP)

Chen et al., (2015) argue that the functionality of dynamic capabilities is likely to be common (e.g., similar BDA technologies powered by AI that can be acquired in the open market); while, "*the value of competitive advantage does not lie in the capabilities themselves, but in the way the resources and capabilities are exploited. Hence, the potential for long-term competitive advantage, lies in 'using dynamic capabilities sooner, more astutely, or more fortuitously than the competition to create resource configurations that have the advantage'*" (Eisenhardt and Martin, 2000, p.1117). Despite the increasing popularity of emerging technologies, like big data analytics and artificial intelligence, there is ambiguity about how the adoption of business analytics impacts firm performance (Akter et al., 2016; Fosso Wamba et al., 2017; Ramanathan et al., 2017; Aydiner et al., 2019; Dubey et al., 2019).

Aydiner et al. (2019) have examined the role of business analytics on operational performance via business processes. Following dynamic capabilities logic, we argue that the use of BDA powered by AI helps organisations develop information processing capabilities (see Srinivasan and Swink, 2018). It enables them to interpret and combine complex information derived from various sources, with managers using this synthesized information to reduce uncertainties regarding demands, capacities, and supply availability (Chen et al., 2015; Dubey et al., 2019). In the absence of such capabilities, organisations need to maintain high inventory or invest in responsive supply chain design, which in turn affects their profit margins. Similarly, we further suggest that insights developed through BDA-AI create opportunities for organisations to reconfigure their resources in ways that help them adapt to dynamic conditions and build better alignment with their partners (Duan et al., 2019). Collectively, such implications of the use of BDA-AI can potentially be reflected in enhanced operational performance. Thus, we hypothesise:

H3: BDA-AI has a significant and positive effect on OP.

2.4.3 Moderating role of environmental dynamism (ED)

The dynamic capabilities view has gained significant attention from management scholars over the past decade (Schilke, 2014; Mikalef et al., 2019 a; Fosso Wamba et al., 2019). Although the dynamic capabilities view has been increasingly used as one of the most important theoretical lenses, the theory has been criticized by some scholars due to poorly defined boundary conditions and its confounding discussion of the effect of dynamic capabilities (e.g., Arend and Bromiley, 2009; Schilke, 2014). Zahra et al. (2006) argue that the inconsistencies in the application of the dynamic capabilities view stem from a lack of clear understanding of the environmental conditions under which the dynamic capabilities operate. However, Helfat and Winter (2011) caution that a turbulent environment is not a necessary condition for dynamic capabilities, which can exist even in stable environments. Hence, in view of such contradictory arguments, it is quite difficult to ascertain the true value of dynamic capabilities for organisational competitive advantage. Amidst such opposing views among scholars, researchers have started to advocate for a more contingent view, positing that the benefits of dynamic capabilities depend not only on the existence of the underlying organisational routines, but also on the context in which these capabilities are deployed (Sirmon and Hitt, 2009). In accounts of dynamic capabilities, scholars have recognised the role of ED as a potentially important contextual variable (Helfat and Winter, 2011; Schilke, 2014; Chen et al., 2015).

Schilke (2014, p. 181) defined ED as "*the volatility and unpredictability of the firm's external environment*". ED is a key factor in DC theory (see Schilke, 2014), which suggests that the differential effects of dynamic capabilities on organisational performance (see Helfat and Winter, 2011; Chen et al., 2015) are contingent on the level of dynamism of the organisation's external environment (Eisenhardt and Martin, 2000). Hence, based on these arguments, we hypothesise:

H4a/b: Environmental dynamism has a positive moderating effect on the paths connecting EO and BDA-AI/OP.

3. Research Design

3.1 Instrument development

We have used cross-sectional data to test our proposed theoretical model (see Figure 1). The data were gathered using a survey-based instrument. The measures used in our study were taken from existing literature. The dimensions were measured on a five-point Likert scale, with anchors ranging from strongly disagree (1) to strongly agree (5) (see Srinivasan and Swink, 2018; Aydiner et al., 2019; Dubey et al., 2019). We have used subjective measures in relation to operational performance, which is a well-accepted practice within organisational research (Stam and Elfring, 2008; Dubey et al., 2019; Sahi et al., 2019a). We pre-tested our questionnaire for face-validity with the help of 25 senior experts drawn from industry. These senior experts were asked to review the questionnaire for structure, readability, ambiguity, and completeness (Dubey et al., 2019). We included the inputs from the senior experts in the final questionnaire. Finally, the constructs were operationalised as reflective constructs. Appendix A lists these constructs, the items used for each measure, and the source from which the items were drawn.

3.2 Data collection

We gathered data in 2018, with the help of the National Association of Software and Services Companies (NASSCOM) and the Federation of Indian Chambers of Commerce and Industry (FICCI). Our cross-sectional survey instrument was sent to over 2,132 manufacturing companies located across India. The database was provided by the FICCI, which is an apex business organisation in India. We validated further using the database of Dun & Bradstreet. To improve our response rate, we followed a modified version of Dillman's (2011) total design test method. The questionnaire was sent to single key informants. As the requirement for participation, respondents had to be a chief technology officer (CTO) or head of technology associated with the adoption and assimilation of emerging technologies within their organisation. We believe that our data collection approach is unique in light of India's unique social and cultural context (see Dubey et al., 2019). Following two waves of data collection, we obtained 256 complete and usable responses, resulting in an effective response rate of 12.01%. We provide the demographic profile of the respondents (firm-level) in Table 1. It includes respondents from eight different industries: pharmaceuticals (10.55%), electrical equipment (9.38%), automotive components (15.23%), machinery and industry equipment (12.89%), food (17.19%), chemicals (15.23%), pulp and paper (10.55%), and consumer goods (8.98%).

Table 1: Profile of Responding Firms

Firm's Industry	**Frequency**	**Percentage**
Pharmaceuticals	27	10.55
Electrical equipment	24	9.38
Automotive components	39	15.23
Machinery and industrial equipment	33	12.89
Food	44	17.19
Chemicals	39	15.23
Pulp and paper	27	10.55
Consumer goods	23	8.98
	N=256	

We examined for the potential for non-response bias by comparing the data collected in two waves, following Armstrong and Overton's (1977) guidelines. Using the t-test we compared two waves: early wave (early respondents) and late wave (respondents who needed a reminder or a longer time to respond to the survey). The results suggest that there is no significant difference between these two waves for each item of the survey ($p>0.05$). Secondly, we tested performance bias by comparing return on assets of the sampled companies with their respective industry median values using paired sample t-tests. We observed no statistically significant differences ($p>0.05$). Based on these two results, we are confident that non-response bias does not pose a serious problem.

4. Data Analysis and Results

4.1 Measurement validation

We performed two steps to examine the nomological validity of our theoretical model using Warp PLS 6.0, which is a PLS technique that has been used for path-analytical models (see Kock, 2019). First, we evaluated the validity and reliability of the measures. Second, we evaluated the structural model to assess the strength of the hypothesized links amongst the variables. We have further assessed the psychometric properties of each construct within the context of the structural model through an assessment of scale composite reliability (SCR), average variance extracted (AVE), and discriminant validity (see Table 2 and Table 3). We observed that all the individual factor loadings are greater than 0.5 (see Appendix B), the scale composite reliability coefficients (SCR) are greater than 0.7, and the average variance extracted (AVE) is greater than 0.5 (see Table 2). Hence, we can assume that convergent validity exists in our theoretical model (Fornell and Larcker, 1981). We further examined the discriminant validity via comparing the square root of AVEs of our constructs with respect to the correlation between two constructs (see Table 3). We note that none of the correlations between the latent constructs were found to be higher than the square root AVE for each individual construct. Hence, we confirm that the constructs of our model possess sufficient discriminant validity. In totality, we can argue that our constructs possess sufficient construct validity. Moreover, the measurement model fit and quality indices were [average path coefficient (APC)=**0.281**, $p<0.001$; average R-squared (ARS)=**0.802**, $p<0.001$; average adjusted R-squared=**0.800**, $p<0.001$; average full collinearity VIF (AFVIF)=**3.047**, acceptable if ≤ 0.5, ideally ≤ 3.3; Tenenhaus GoF= **0.604**, small≤ 0.1, medium ≥ 0.25, large ≥ 0.36]. Hence, these statistical results suggest that the model fit is good (Sarstedt et al., 2014; Moqbel and Kock, 2018).

Table 2: Loadings of the indicator variables (Cronbach's alpha, SCR and AVE)

Construct	Items	Factors loadings (λi)	Variance	Error (ei)	Scale composite reliability (SCR)	Average variance extracted (AVE)
Entrepreneurial orientation (EO) (α=0.87)	EO1	0.78	0.61	0.39	0.90	0.56
	EO2	0.70	0.49	0.51		
	EO3	0.83	0.69	0.31		
	EO4	0.77	0.59	0.41		
	EO5	0.69	0.47	0.53		
	EO6	0.72	0.52	0.48		
	EO7	0.73	0.53	0.47		
Big data analytics-artificial intelligence (BDA-AI) (α=0.92)	BDA-AI1	0.74	0.55	0.45	0.92	0.56
	BDA-AI2	0.67	0.45	0.55		
	BDA-AI3	0.78	0.61	0.39		
	BDA-AI4	0.76	0.57	0.43		
	BDA-AI5	0.79	0.62	0.38		
	BDA-AI4	0.73	0.53	0.47		
	BDA-AI5	0.76	0.58	0.42		
	BDA-AI8	0.70	0.49	0.51		
	BDA-AI9	0.79	0.63	0.37		
Operational performance (OP) (α=0.9)	OP1	0.67	0.45	0.55	0.90	0.50
	OP2	0.58	0.34	0.66		
	OP3	0.75	0.56	0.44		
	OP4	0.57	0.32	0.68		
	OP5	0.73	0.53	0.47		
	OP6	0.76	0.57	0.43		
	OP7	0.76	0.57	0.43		
	OP8	0.75	0.57	0.43		
	OP9	0.78	0.61	0.39		
Environmental dynamism (ED) (α=0.84)	ED1	0.82	0.68	0.32	0.84	0.58
	ED2	0.82	0.67	0.33		
	ED3	0.86	0.73	0.27		
	ED4	0.51	0.26	0.74		

Table 3:Inter-construct correlations

	EO	**BDA-AI**	**OP**	**ED**
EO	***0.95***			
BDA-AI	0.57	***0.96***		
OP	0.59	0.61	***0.92***	
ED	-0.04	0.01	-0.01	***0.87***

4.2 Common method bias

The common method bias (CMB) is often associated with cross-sectional survey design used for data collection (Ketokivi and Schroeder, 2004; Guide and Ketokivi, 2015; Kock, 2015a). Kock (2015a, p.2) argues that "*the instructions at the top of a questionnaire may influence the answers provided by the different respondents in the same general direction, causing the indicators to share a certain amount of common variation*". Podsakoff et al. (2003) argue that CMB may also result from social desirability associated with answering questions in a particular way, again causing the indicators to share a certain amount of common variation. Since we have used single informant cross-sectional survey design to gather data, there is the potential for CMB. So to reduce the potential effects of CMB, we designed our questionnaire using different scale formats and anchors of independent, moderating, and dependent variables. Moreover, we tested for CMB in various ways. Firstly, we performed a conservative version of Harman's one factor test to verify that the results are not biased because of a single respondent (Podsakoff and Organ, 1986). The results from this test show that the single factor explains 42.06% of the total variance, demonstrating that CMB is not a major concern. Secondly, we tested for CMB using the correlation marker technique (Lindell and Whitney, 2001). We noted minimal differences between adjusted and unadjusted correlations. Moreover, the significance of the correlations did not change. In totality, we can conclude that CMB has no significant effect on our study.

Before we discuss our hypothesis testing, causality is an important aspect that should be examined (see Abdallah et al., 2015; Guide and Ketokivi, 2015; Dubey et al., 2019; Kock, 2015b). Following Kock's (2015b) suggestions, we examined the nonlinear bivariate causality direction ratio (NLBCDR). The acceptable value should be ≥0.7. In our case, we note that NLBCDR=0.79. Hence, causality is not a major concern in our study.

4.3 Hypotheses testing

Figure 2 presents the estimates obtained via PLS SEM analysis. PLS does not assume data to be normally distributed. Hence, we have not performed traditional parametric-based techniques for significance tests. PLS uses a bootstrapping procedure to estimate standard errors (SEs) and the significance of parameter estimates (Peng and Lai, 2012; Dubey et al., 2019). The PLS path coefficients and their corresponding values of "p" have been reported in Table 4 (H1-H3) and Table 5 (H4a and H4b). The paths EO→BDA-AI (β=0.9; $p<0.001$), EO→OP (β=0.42; $p<0.001$), and BDA-AI→OP (β=0.52; $p<0.001$) are positively linked. Hence, our hypotheses H1-H3 were supported. The control variables (CV), organisational size (OS), and industry type (IT) do not have significant effects in this model (see Table 4). Next, our hypothesis H4 was tested for the moderation effect of ED on the paths joining BDA-AI (H4a) and OP (H4b). H4a (β=0.32; $p<0.001$) and H4b (β=0.12; p=0.031) were found to be supported (see Table 5). Then we examined the explanatory power of the research model based on the explained variance (R^2) of the endogenous constructs of our model (see Figure 2) on BDA-AI (0.80) and OP (0.81).

Further, we examined the effect size of predictor (EO) using Cohen's f^2 formula (Cohen, 1988). According to Cohen (1988), the f^2 values of 0.35, 0.15, and 0.02 are considered large, medium, and small. Consequently, we find the effect sizes of EO on BDA-AI (0.9), EO on OP (0.42), and BDA-AI on OP (0.52). Further, to predict the model's capability to predict, we used Stone-Geisser's Q^2 for endogenous constructs. In our case, we noted the Q^2 for BDA-AI (0.73) and OP (0.81), indicating high predictive relevance (Peng and Lai, 2012).

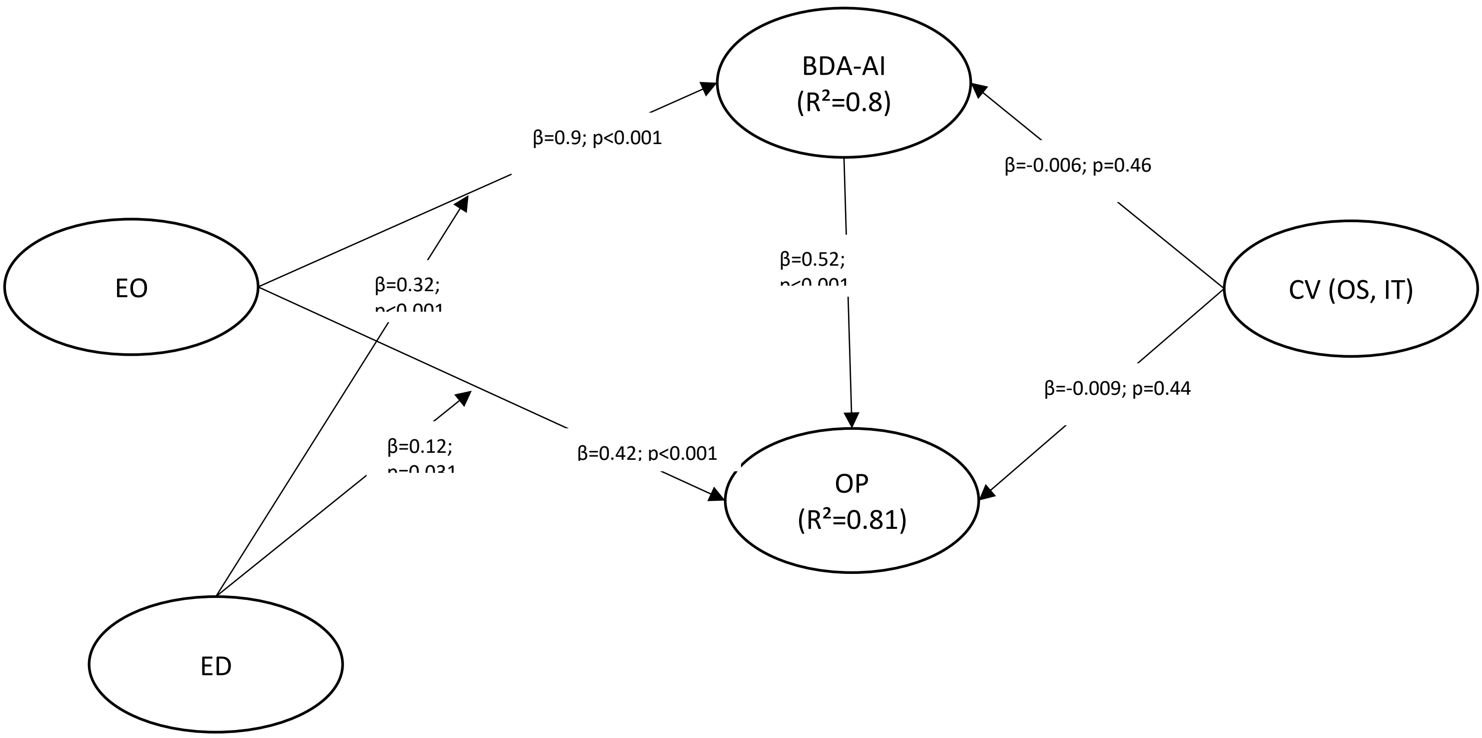

Figure 2: Final SEM model

Table 4: Structural estimates (H1-H3)

Hypothesis	*Effect of*	*Effect on*	*β*	*p*	*Result*
H1	EO	BDA-AI	0.9	<0.001	supported
H2	EO	OP	0.42	<0.001	supported
H3	BDA-AI	OP	0.52	<0.001	supported
Control variables (CV)					
	OS and IT	BDA-AI	-0.006	0.46	Not significant
	OS and IT	OP	-0.009	0.44	Not significant

Table 5: Structural estimates (H4a and H4b)

Hypothesis	*Effect of*	*Effect on*	*β*	*p*	*Result*
H4a	EO* ED	BDA-AI	0.32	<0.001	supported
H4b	EO*ED	OP	0.12	0.031	supported

5. Discussions

Our results paint an interesting picture of the associations among entrepreneurial orientation (EO), big data analytics powered by artificial intelligence (BDA-AI), operational performance (OP), and environmental dynamism (ED) in dynamic markets. Table 4 and Table 5 provide support or non-support of the hypotheses generated in our study. In total, these findings have immense implications for theory and practice. The availability of data and data processing capability are the two cornerstones of the big data analytics capability of any organisation (Srinivasan and Swink, 2018). Accordingly, our study attempts to provide an empirical support that the EO and ED are significantly associated with developing BDA-AI. The previous studies on big data analytics, artificial intelligence, and operational performance, especially in information systems research, have particularly focused on the four Vs (velocity, volume, variety, and value) of data (Chen et al., 2015; Duan et al., 2019). However, some scholars have acknowledged the role of external lateral relations or external linkages, with the supply chain partners able to help enhance supply chain visibility (see Gunasekaran et al., 2017; Srinivasan and Swink, 2018). It is well understood that competitive advantages stem from the ways in which technologies are used, rather from the technologies themselves (Barratt and Oke, 2007; Chen et al., 2015; Srinivasan and Swink, 2018; Dubey et al., 2019). Our study attempts to address gaps noted by some leading operations management scholars (see Joglekar and Levesque, 2013; Hora and Dutta, 2013; Krishnan, 2013). Joglekar and Levesque (2013) argue that the role entrepreneurial organisations play in taking risks, while exploiting and exploring new types of business models to stimulate technology commercialisation and growth, has been recognised in the business press. However, despite significant attention from the entrepreneurship and operations management communities, their focus tends to differ. Hence, through our study we have attempted to address the question: *What are the distinct and joint effects of EO and BDA-AI on operational performance?* And more specifically: *What are the effects of ED on the paths joining EO and BDA-AI/OP?*

The findings of our study indicate that three entrepreneurial traits: “pro-activeness”, “risk taking”, and “innovativeness” are vital to sensing dynamic changes in the market. Moreover, the firms which are entrepreneurially oriented can simultaneously explore and exploit emerging technologies like BDA-AI to improve their decision-making ability, which further helps improve operational performance. These findings are consistent with the established literature that EO capability is an important component of organisational management, particularly within the domains of technology and operations management (Levesque and Joglekar, 2018; Canakoglu et al., 2018; Sahi et al., 2019a). Furthermore, we view EO as a dynamic capability that brings temporary competitive advantage to the organisations (Zahra et al., 2006; Wu, 2007; Sahi et al., 2019a). Consistent with this view of dynamic capabilities, we show that ED moderates the way in which EO influences the adoption of BDA-AI and operational performance. Particularly, we observe that EO influences the use of BDA-AI driven decision-making in dynamic environments, in accordance with our hypothesis. On the other hand, we observe the influence of EO on OP - although it is a positive relationship - is less pronounced in more dynamic environments. This finding contrasts with our proposed hypothesis; however, as we assess this result, we suspect a potential for bias in this observation. There are several reasons EO may not be as effective to OP as the adoption of BDA-AI in highly dynamic situations. Firstly, the improvement in OP due to efficient and effective decisions may take some time. Hence, managers may understand the differential effects of the adoption of BDA-AI on their decision-making abilities and the overall impact on operational performance over a time. Secondly, we have assumed a linear effect of the ED on the paths joining EO and BDA-AI/OP. Following Schilke’s (2014) arguments, dynamic capabilities have differential performance effects in very stable and very dynamic settings and strongly positive ones in moderately dynamic environments. In such cases, the nonlinear moderating effects of ED may offer nuanced understanding. Together, these complex effects offer some interesting implications for advancing theory and managerial practice.

Informed by recent works (see, Terwiesch, 2019; Fisher et al. 2019), our main contributions are as follows:

5.1 Implications for theory

Following Fisher et al.’s (2019) arguments, we have examined the operational problems that matter to companies. For, instance artificial intelligence driven big data analytics capabilities has been the subject of debate during the last few years in the context of improving operational performance. However, most of the studies have either focused on developing algorithms or lack desired scientific rigour needed for an empirical research (see, Fisher, 2007; Terwiesch, 2019). We address these limitations by undertaking a rigorous empirical study focused on enhancing our understanding of how activities such as big data analytics driven by artificial intelligence can affect performance.

Our study makes two useful contributions to the literature by integrating entrepreneurship with operations management and information systems management. Firstly, we have examined the direct association between EO and BDA-AI. We have grounded our assumption in a dynamic capabilities view of the organisations. Our findings reveal that three entrepreneurial traits, “pro-activeness”, “risk taking”, and “innovativeness”, are desirable components in making decisions related to the adoption of emerging technologies. To understand the adoption of technology, previous scholars have used theory of reasoned action (Ajzen and Fishbein, 1970), theory of planned behaviour (Ajzen, 1991), or technology acceptance model (Davis, 1989). However, the role of entrepreneurial orientation on the adoption of emerging technology, like BDA-AI, provides an interesting perspective. Thus, we argue that EO is a desired capability that prepares the organisation to invest in emerging technologies that may help it cope with changes in the external environment. Secondly, by investigating the moderating effects of ED on the paths EO-BDA-AI/OP, our findings suggest that EO has differential effects on BDA-AI and OP under varying degrees of ED. Grounded in contingency theory (CT), our findings reveal that a moderate level of environmental dynamism is conducive to entrepreneurial orientation having a significant impact on the adoption of BDA-AI and OP.

5.2 Implications for managerial practice

Operations management research has a long-standing tradition of providing mathematical models to help managers improve decisions. For instance inventory, transportation, revenue and labour staffing are some of the areas in which classical models have positively impacted on the operations management practices (Fisher et al. 2019). It is well understood that data analysis is needed as an input in order to implement these models. Most of the effort in developing these models has traditionally focused on the optimisation of stochastic models, though in the last decade empirical studies have gained major attraction within operations management communities (Fisher, 2007; Sodhi and Tang, 2014). New data sources and the development of psychometrics/econometrics methods permit more sophisticated modelling of the behaviour of customers and employees, which are then often used to enrich the models and algorithms. Our study is informed by Terwiesch (2019) and Fisher et al.’s (2019a) arguments that a key aim of theory-driven study is to enhance its relevance to practice and to further examine the divergences in theory and practice. Hence, we have attempted to discover some managerial actions that may be contrary to our findings or be inconsistent with our theory. For instance, the major challenge that organisations face today is rapidly changing environments. Moreover, the expectations and latent needs of customers often create pressure on supply chain network design (Fawcett and Waller, 2014).

Our results suggest that investments in building three important entrepreneurial traits of the organisation - “pro-activeness”, “risk-taking”, and “innovativeness”, alongside BDA-AI - are strategically justified in many organisational environments. In simple words, managers need to be entrepreneurially oriented to build and exploit these dynamic capabilities in order to gain competitive advantage. As some of the routines develop accidentally, managers need to be patient when investing in these dynamic capabilities. Specifically, it is important to understand where and how to build BDA-AI as well as how to exploit BDA-AI to gain competitive advantage. Moreover, environmental dynamism could influence the way EO can impact the adoption of BDA-AI and OP. Therefore, managers need to understand how varying degrees of environmental dynamism can influence the effectiveness of the adoption of BDA-AI and impact on operational performance. The study’s empirical findings offer a nuanced understanding of EO and BDA-AI which, in turn, helps clarify the role ED plays in influencing the efficacy of dynamic capabilities. Hence, the data-driven research we have undertaken in our study provides additional benefits by giving credibility to our prescriptions for practitioners and further useful information to help gauge their implementation.

5.3 Limitations and further research directions

We note several limitations of our study. Firstly, while our dataset included a broad range of manufacturing organisations representing a variety of industries, we caution our readers that they should evaluate the results of our study in the light of its limitations. Therefore, readers must carefully generalise the results. Hence, this offers further opportunities to scholars to scrutinise the findings of our study in other settings, possibly including different industries, countries, or time periods, to ensure higher levels of variance of environmental dynamism in the dataset. Future studies could also determine whether the moderating role of the ED on the relationship between EO and BDA-AI/OP also extends to other environmental characteristics, such as organisational culture or organisational structure. Secondly, the theories we employed use causal terms to explain the relationships included in the proposed theoretical model; however, the cross-sectional research design used does not fully establish the causality. For future studies, scholars may conduct a longitudinal study that may help to understand how EO influences the adoption of BDA-AI. A longitudinal study may also offer in-depth understanding of how the three traits of EO – “pro-activeness”, “risk-taking”, and “innovativeness” - may differentially influence the adoption of BDA-AI for superior operational performance. Further, longitudinal data may reduce the potential bias resulting from single informant cross-sectional design. Finally, we believe that replication is an important way to further establish the validity of empirical results and future studies might address our research questions in different contexts, with the aim of providing better understanding by using mixed-research design.

6. Conclusion

Our study is inspired by recent debate regarding how empirical research can help to shape the growing operations management field of enquiry (see, Fisher, 2007). The results of empirical studies have played an important role in improving decision making abilities of operations managers. By grounding our study in how work is actually done at the operational level we have sought to examine any degree of divergence that exists between theory and practice. In this way we evaluate future strategies to calibrate managerial actions or to refine existing theories. Our key result is that the traits of entrepreneurialism – pro-activeness, risk taking and innovativeness have a vital importance in allowing companies to sense dynamic market changes. The entrepreneurial orientation allows companies to enhance their performance by improving their decision-making ability through exploiting BDA-AI.

Our study addresses an important gap in the literature as to whether EO influences the adoption of BDA-AI, which consequently impacts operational performance, and, moreover, how ED can explain the differential effects of EO on the adoption of BDA-AI and operational performance. Our study is innovative in that it integrates three important fields of management: entrepreneurship, operations management, and information systems management. The findings provide a theory-based, nuanced understanding of the impact of three traits of EO - “pro-activeness”, “risk-taking”, and “innovativeness” - on the adoption of BDA-AI for decision-making in dynamic environments and, in doing so, offer some unique contributions to theory and managerial practice.

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Appendix A: Construct Operationalization, Derivation, and Measures

Construct and Derivation	**Measures**
Entrepreneurial orientation (EO) (Matsuno et al., 2002)	To what extent our organisation: (1 = strongly disagree, 2 = disagree, 3 = not sure, 4 = agree, 5 = strongly agree) *Pro-activeness* Firmly believe that a change in market creates positive opportunity for us [EO1] Team members tends to talk more about opportunities rather than problems [EO2] *Risk-taking* Value the orderly and risk-reducing management process much more than the leadership initiatives for change [EO3] Senior managers like to "play it safe" [EO4] Top managers around here like to implement plans only if they are certain [EO5] *Innovativeness* When it comes to problem solving, we value creative solutions more than the solutions of conventional wisdom [EO6] Top managers encourage the development of innovative marketing strategies, knowing well that some will fail [EO7]
Big data analytics powered by artificial intelligence (BDA-AI) usage (Chen et al., 2015)	To what extent your organisation implemented *BDA-AI* in each area: (1 = strongly disagree, 2 = disagree, 3 = not sure, 4 = agree, 5 = strongly agree) Suppliers analysis [BDA-AI1] Customer behaviour analysis [BDA-AI2] Inventory planning[BDA-AI3] Warehouse operations improvements [BDA-AI4] Process/equipment monitoring [BDA-AI5] Transportation planning [BDA-AI6] Demand forecasting [BDA-AI7] Human resource management [BDA-AI8] Costing [BDA-AI9]

Operational performance (OP) (Chen et al., 2015 ; Aydiner et al., 2019)	To what extent our organisation has achieved with respect to major competitors: (1 = strongly disagree, 2 = disagree, 3 = not sure, 4 = agree, 5 = strongly agree) Revenue growth over the last three years [OP1] Market share growth in last three years [OP2] Return on investment [OP3] Cash flow from operations [OP4] New product/service development [OP5] Return on capital employed [OP6] Profit to revenue ratio [OP7]
Environmental dynamism (ED) (Chen et al., 2015)	What is the rate of change (volatility) in your business unit's competitive environment relative to change in other industries? (1 = very stable, 2 = stable, 3 = about average for all industries, 4 = volatile, 5 = very volatile). (i) The rate at which your customer's product/service needs change [ED1] (ii) The rate at which your supplier's skills/capabilities change [ED2] (iii) The rate at which your competitors' products/ services change [ED3] (iv) The rate at which your firm's products/services change [ED4]

Appendix B: Exploratory Factor Analysis Output

	EO	BDA-AI	OP	ED	Type	SE	P value
EO1	0.78				Reflect	0.055	<0.001
EO2	0.70				Reflect	0.056	<0.001
EO3	0.83				Reflect	0.054	<0.001
EO4	0.77				Reflect	0.055	<0.001
EO5	0.69				Reflect	0.056	<0.001
EO6	0.72				Reflect	0.055	<0.001
EO7	0.73				Reflect	0.055	<0.001
BDA-AI1		0.74			Reflect	0.055	<0.001
BDA-AI2		0.67			Reflect	0.056	<0.001
BDA-AI3		0.78			Reflect	0.055	<0.001
BDA-AI4		0.76			Reflect	0.055	<0.001
BDA-AI5		0.79			Reflect	0.055	<0.001
BDA-AI4		0.73			Reflect	0.055	<0.001
BDA-AI5		0.76			Reflect	0.055	<0.001
BDA-AI8		0.70			Reflect	0.055	<0.001
BDA-AI9		0.79			Reflect	0.055	<0.001
OP1			0.67		Reflect	0.056	<0.001
OP2			0.58		Reflect	0.057	<0.001
OP3			0.75		Reflect	0.055	<0.001
OP4			0.57		Reflect	0.057	<0.001
OP5			0.73		Reflect	0.055	<0.001
OP6			0.76		Reflect	0.055	<0.001
OP7			0.76		Reflect	0.055	<0.001
OP8			0.75		Reflect	0.055	<0.001
OP9			0.78		Reflect	0.055	<0.001
ED1				0.82	Reflect	0.054	<0.001
ED2				0.82	Reflect	0.054	<0.001
ED3				0.86	Reflect	0.054	<0.001
ED4				0.51	Reflect	0.057	<0.001