Migration Letters

Volume: 21, No: 3, pp. 1330-1353

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)
www.migrationletters.com

The Transformative Impact of Business Analytics Adoption on Competitive Advantage in the E-Commerce Industry: A Strategic Perspective

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Abstract

In the current era marked by disruption and uncertainty, the reliance on top executives' intuition, experience, and education necessitates augmentation with pertinent data to enhance firm competitiveness. Acknowledging the pivotal role of data in business, companies of varying sizes recognize the significance of data-driven and purpose-driven business analytics for gaining a competitive edge. Despite this awareness, organizations often underutilize data to foster a competitive advantage. This study delves into the strategic approach of maximizing data utilization, referred to as business analytics adoption (BAA), as a transformative catalyst for business growth and the establishment of competitive advantages. The primary objective of this research is to investigate the impact of the Technological, Organizational, and Environmental (TOE) framework, mediated by business analytics adoption (BAA) and dynamic capability, on achieving competitive advantage (CA) performance, specifically within the context of an E-commerce company. The study involved 327 E-commerce firms. The collected data underwent processing and analysis through Structural Equation Modeling (SEM). The findings of this study reveal that the technological, organizational, and environmental factors positively and significantly influence business analytics adoption and dynamic capability. Business analytics adoption serves as a mediator between technological factors and dynamic capability, as well as organizational factors and dynamic capability. Additionally, dynamic capability mediates the relationship between business analytics adoption and competitive advantage. Both business analytics adoption and dynamic capability exhibit positive and significant effects on competitive advantage.

Keywords: *TOE framework, business analytics adoption, dynamic capability, competitive advantage, e-commerce, industry 4.0.*

1. INTRODUCTION

The fourth industrial revolution brought about radical changes in the human way of life. The advent of artificial intelligence has enhanced innovations and introduced extremely new realities to the future of mankind (Davenport, Guha, Grewal & Bressgott, 2020). To this end, the World Economic Forum (2020) spawned the Centre for the New Economy and Society initiative for public and private organizations to advance studies in data science, shape new models and standards, and drive scalable action for systemic change to deepen our understanding of our new future. Per this initiative's findings, firms worldwide should start changing the way they look at the world today to foster competitive advantage tomorrow (Reeves & Deimler, 2011). As the world moves on from

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archaic resources like gold or oil and many more abstract and intangible assets like data and information, successful exploration and management of these resources is growing ever more vital. Primarily, organizations have fully understood that purpose-driven and data-driven are crucial. Nevertheless, companies do not prepare enough for this challenge and enter industry 4.0 by nature. The ability to transfer knowledge of extensive use of data and information from individuals (tacit) to individuals (tacit) or from individuals to organizations (tacit to explicit) is, for instance, still lacking. This is because the ability and skills to maximize and optimize the extensive use of data and information do not reside within the organizations (Rehman, Chang, Batool, Wah, 2016; Sivarajah, Kamal, Irani, Weerakkody, 2017). These skills and abilities are still inherent to individuals and have not yet been transmitted and disseminated properly throughout the organizations (Sivarajah et al., 2017).

Behl (2020) later empirically found that big data analytics capability positively affected firm performance and competitive advantage. Since the data were collected from the startups in which the big data was utilized for their business purposes, we can say that this big data analytics capability is essentially business analytics capability. In other words, business analytics capability should also affect the firm's competitive advantage. Nonetheless, the existing literature has not yet empirically examined this effect, and consequently, examining this effect is the objective of this study. Behl (2020) further argued that business analytics capability and big data analytics capability are rooted in dynamic capability, which captures the overall firm's capability to cope with its dynamic environment. In addition, Holsapple et al. (2014) contended that business analytics capability is a result of the decisional paradigm of adopting business analytics. The question then becomes, if the decision to adopt business analytics yields business analytics capability, will the same decision result in dynamic capability? Relating this question to the said objective of this study, will business analytics directly and or indirectly (via dynamic capabilities) affect competitive advantage? These two questions have also not been addressed in the existing literature, and thus addressing such questions is the subsequent objective of this study.

Meanwhile, Teece, Pisano, and Shuen (1997: 516) defined dynamic capabilities as "the firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments." In other words, dynamic capabilities are built as a response to the fluctuated context the firm is in. Tornatsky and Fleischer (1990) introduced technology-organization-environment (TOE) as a framework and theoretical lens to examine contextual factors. Technology, for instance, is a resource enabler that supports the firm in configuring resources and capitalizing opportunities to adapt to the fast-changing environment. Technology benefits and influences the firm's business analytics through the development of innovation that immerses into products and services. Technology determines how fast the firm can adapt to uncertain conditions, as well as encourages the firm to explore and sense new opportunities across the market and could lead the firm to marketplace acceptance as the first-mover (Wilden, Gudergan, Nielsen & Lings, 2013). Technology helps simplify enormous amounts of data and information, which in turn influences the dynamism and the intensity of global competition of the firm. It is the technology that eventually determines how business analytics is going to be adopted.

In TOE framework, organizational factors such as strong leadership from the top management team, reward system (Lawson & Samson, 2001), capabilities in managed cross-functional teams, and organizational structure and process. Organizational factors are an internal context that determines how things are done in the firm, including how business analytics adoption is going to be implemented. Top management support is required for organizational restructuring and process reengineering, which subsequently affects the firm's business analytics adoption. Top management support is also essential in deciding whether the organization is going to adopt business analytics. The same is true for organizational structure and process, which represents the coordination mechanism within the firm. Organizational structure and process affect how quickly and flexibly the firm utilizes its competencies to respond to fluctuated contexts, as well as to streamline huge amounts of data and information. In short, organizational structure determines the firm's adoption of business analytics.

The environment is the classical external contextual factor in TOE framework that indicates the extent to which the industry or market, the society, and the government are dynamics. A turbulent market, for example, forces the firm to quickly integrate, build and reconfigure its competencies to respond to such turbulency. In addition, a turbulent market presents the firm with continuous and vast amounts of data and information that need to be well organized to provide value for the firm. The same is true for the rapid shift of society because of the growth of the Internet of things that requires the firm to develop its business analytics adoption to establish dynamic capability. In sum, referring to Maroufkhani, Tseng, Iranmanesh, Ismail, and Khalid (2020), technology, organization, and environment are enablers and determinants of business analytics adoption. Furthermore, technology, organization, and environment direct the firm on how business analytics is going to be adopted. Nevertheless, there has been a lack of research that directly relates TOE factors to business analytics adoption. Consequently, examining such direct relations is the objective of this study.

Indonesia, as a research context, has the fastest growing E-commerce in the world, with more than 100 million internet users (Merchant Machine, 2019). This situation has led to a rapid increase in the amount of structure and unstructured data in Indonesia. With the abundance of data and information flows, Indonesia is preparing policies and actions through "One Data Indonesia." Such government initiative opens the door for the prevalence and environmental significance of business analytics adoption. The adoption of business analytics integrates business understanding and data understanding to leverage the data for decisions and actions. The transfer of new knowledge from data grows exponentially along with their insight opportunities. Adequate capabilities and technology are essential to pursuing these new opportunities. Data can be one of Indonesia's current treasures: today, data is more valuable than oil. The inevitable growth of data and information makes its use even more vital. Skills and abilities are needed to optimize and increase value to improve the welfare of individuals, companies, and nations.

2. LITERATURE REVIEW

2.1. Technological, Organizational, and Environmental

Technological, organizational, and environmental (TOE) are contextual factors that are put together as a framework by Tomatzky and Fleischer (1990) to study the adoption of technological innovation. Technological factor concerns not only information technology (IT) assets but also technology complexity and compatibility. Complexity is associated with difficulty in understanding and using the technology, while compatibility is related to the consistency of technology with the existing values, past experiences, and needs of potential adopters (Rogers, 2003). Organizational factor involves top management support for information and communication technology (ICT) program and its integration with the business process (Young & Jordan, 2008), as well as encompass data resource management (K. Ramamurthy, Sen, & Sinha, 2008) and expenses and efforts (such as organizational restructuring and process re-engineering) incurred for implementing technology (Chau & Hui, 2001). Environmental factor mainly focuses on perceived industry pressure and perceived government pressure (Kuan & Chau, 2001).

In a further development, Zhu and Kraemer (2005) considered TOE as an important antecedent to understanding the diffusion of e-business, while Weng and Lin (2011) employed TOE framework to analyze the determinants of the adoption of green innovation technology by small and medium-sized enterprises (SMEs). Moreover, Rahayu and Day (2015) developed a model based on TOE framework to investigate factors that influence SMEs in developing countries to adopt e-commerce. Then Puklavec, Oliveira & Popovic (2018) suggested TOE as determinants for business intelligence system adoption stages. In more recent studies, Kumar and Krishnamoorthy (2020) elaborated TOE framework for investigating business analytics adoption of the firm, while Abed (2020) used TOE as the theoretical framework to examine the factors that affect the intention of SMEs to utilize social commerce as a business tool. Technological, organizational, and environmental are the TOE framework factors developed by Tomatzky and Fleischer (1990). There are three dimensions of technological factors: Complexity, IT Assets, and Compatibility. Organizational factors influence the business analytics adoption to impact the previous and existing organizational learning the future actions in technology management (Erevelles et al., 2016; Nayak et al., 2019).

There are three main dimensions of organizational factors in the TOE framework: top management support, organizational data environment, and perceived cost. Top Management Support devotes their time to the information system (IS) program in proportion to its cost and potential, reviewing plans, following up on results, and facilitating the management problems involved with integrating new technology with the business management process (Young and Jordan, 2008). An organizational data environment is how an organization can manage the data resources within the entire organization (Ramamurthy et al.,2008). The expenses of implementing necessary technologies in organizations, efforts devoted to organizational restructuring, and process re-engineering related to the perceived cost dimension. (Chau and Hui, 2001). In TOE framework, external pressure and industry type are the two dimensions of environmental factors. External pressure is the influence of the external business environment (Kuan and Chau, 2001) that affects business analytics. Using environmental factors to improve business analytics inside and outside an organization will increase process performance and the firm’s competitive advantage.

2.2 The Relationship Between Business Analytics and Dynamic Capability

Business analytics helps to shed light on how to employ dynamic capabilities perspective to detect, anticipate and respond to an uncertain environment. Teece (2007) characterized dynamic capabilities as the capacity to sense opportunities and threats, seize opportunities and maintain competitiveness through transforming assets. To understand environmental changes, Teece suggested that dynamic capabilities require ‘some kind of analytical framework’ (Teece, 2012; Teece, 2007). The dynamic capability model of sensing, seizing and transforming (Kump e al, 2019; Teece, 2007) as a robust dimension can be affected by business analytics. Business analytics influence sensing the internal and external opportunity, i.e., detecting the opportunities for efficiency improvement or effectiveness in the company, sense the requirement new way of business works, sensitive to internal threats and opportunities and inefficiencies, identification on current business processes opportunities to improve effectiveness or efficiency in the company (Rijmenam et al., 2019). Besides, sensing the opportunities and threats in the environment can be enhanced through the adoption of business analytics, opportunities identification to the change of organizations are driven by awareness of our environment, market condition, prepare actionable options based on surrounding of the business. Capability on business analytics will enhance seizing capability to develop agreement among relevant stakeholders, build consensus among relevant stakeholders, formulate, and develop a viable and effective action plan, create a capitalize strategy on the situation, and make a decision effectively about which course of action to pursue, quickly decide on the best course of action, decide on the appropriate course of action (Rijmenam et al., 2019). In transforming and change capability, business analytics capability helps on activity, business processes change with adapt rapidly into business processes to competitive changes (Torres et al., 2018).

Business analytic capability is a critical issue in electronic commerce. Every company should catch up with and has a ready-to-cope attitude. Most e-commerce companies face this industry by nature without appropriate and well plan skills and capabilities. These companies realize the critical asset of big data. Nevertheless, they have no capabilities to know how to optimize and have no competence in business analytic capabilities. Business analytics adoption enhances dynamic capability to sense immediate problems and sales opportunities. People analytics will become an enabler to sales representatives on location (Rijmenam et al., 2019). Vidgen et al. (2017) advise that capability of business analytics of an organization is perceived as an enhancer between the access (internal and external) data the organization generates and the value the organization may leverage through a better decision from that data (Vidgen et al., 2017). Business analytic capabilities have broader implications for improving the firm's dynamic capability through value creation. Vidgen et al. (2017) explain how business analytics capabilities will enable a company to manage its resources by building organizational data and skills and overcoming analytical and technical skills shortages. The important challenges for managers in developing business analytics are how to use and align the current IT platforms and fit with big volumes of data to sense, anticipate, and have a quick response strategically. This challenge will enhance the firm ability to produce credible analytics, manage data processes, manipulate data, and in the end, will improve dynamic capability.

2.3 The Relationship Between Business Analytics Adoption and Competitive Advantage

The foundation for the growing research related to industry 4.0 is mainly on adding value to the customers (demand-pull) and the processes (technology-push) (Frank, Mendes, Ayala, & Ghezzi, 2019). To add value, organizations need data and information on what value could be added that is translated into higher quality products and services with lower production costs, which in the end is translated into a competitive advantage (Mikalef, Pappas, Krogstie & Giannakos, 2019). However, these data and information must be further examined and analyzed before they are utilized to create additional value. The process of acquiring, examining, analyzing, storing, and using the data and information is known as business analytics (Holsapple et al., 2014). Organizations that adopt business analytics "is concerned with the extensive use of data, statistical, and qualitative analysis, explanatory and predictive models and fact-based management to derive decision and actions" (Davenport & Harris, 2007, p.7).

According to Aydiner, Tatoglu, Bayraktar, Zaim, & Delen (2019), there are four dimensions of business analytics adoption: data acquisition and processing, prescriptive analytics, predictive analytics, and descriptive analytics. Lepenioti, Bousdekis, Apostolou, & Mentzas (2020) argued that prescriptive analytics was about finding the best course of action in analyzing data and information and is often considered the next step toward increasing data analytics maturity, leading to optimized decision-making ahead of time for business performance improvement. Drawing from classical statistics, predictive analytics is used to predict the future by analyzing the current and historical data and information and making it into a model (Kumar & Garg, 2018). Meanwhile, prescriptive analytics answers such questions as, "What should I do?" and "Why should I do it?" (Lepenioti et al., 2020). Business analytics is frequently referred to big data analytics as data and information collected and processed are in a large amount (Duan & Xiong, 2015; Pappas et al., 2018; Vassakis et al., 2017). Business analytics adoption creates a competitive advantage through innovation differentiation and market differentiation (Zhou, Brown, & Dev, 2009). Competitive Advantage is defined as the capacity of a firm to enhance the value of its products, decrease the cost of its products, and expand its business presence or benefit. (Grupe & Rose, 2010; Mcgahan & Porter, 2019; Porter, 1990). In searching for a competitive advantage, firms face competitive dynamics, which present new opportunities and possibilities for innovation. In other words, as Ireland and Webb (2007) denoted, firms can create a competitive advantage through the exploitation of such opportunities and streams of innovation.

In the era of big data, the exploitation and exploration opportunities through innovation require firms to support and develop data-oriented management systems to make sense of the increasing volumes of data and address the need to create an understanding of the business value and build competitive Advantage (Kiron and Shockley, 2011). Business needs data and analytics to provide benefits for organizations by enabling improvements to business processes and firm performance and creating competitive Advantage (Davenport and Harris, 2007). As an example, the process of understanding and meeting customer needs related to the firm's marketing and sales activities is highly dependent on business insights gathered from the availability of data and information. These activities will ultimately create a competitive advantage by generating excellent quality, economies of scale, and economies of scope. The economies of scale are the first way organizations drive to achieve competitive Advantage through cost efficiencies against their peers.

HYPOTHESES DEVELOPMENT

In this section, the research hypothesis is developed based on the previous study in the literature on the business analytics context. The research model is presented in figure 1. In this model, the TOE framework will enhance the firm competitive advantage through business analytics adoption and other path mediated by dynamic capability. TOE is the determinant factor of business analytics adoption, and competitive advantage is a consequence of output. Therefore, in this context, the researcher formalizes the circumstances into a hypothesis as follows:

H1: Technological factor positively and significantly affects the business analytics adoption

Technology is one of the key factors of business analytics to create new products using high-volume, high-speed, and real-time customer activity data (Conboy et al., 2020). The availability and character of technology in an organization affect the way that a company adopts business analytics. The complexity of technology is related to how easily the innovation will be implemented once adopted. When the learning process to use business analytics is difficult for employees, companies tend to delay the adoption. The procedure for learning and implementing the technology should be simple and easy to understand. Besides, Roger (1983) argues that some of the characteristics of technology that influence adoption are related to relative advantage. Relative advantage characteristic means whether the improvement of the new technology will be better than the previous generation of technology. Technological factors dimension consist of complexity, IT assets, and compatibility. These three main dimension affects the decision of an organization to adopt business analytics. The technology complexity and assets comprise the human resources competency and Information Technology infrastructure to rapidly adopt the adoption of business analytics. The previous research has also supported the result that IT assets as a significant factor in technology adoption (Gangwar 2018). The compatibility of business analytics with business needs is a critical determinant for business analytics adoption (BAA). The BAA implementation starts with gathering the business requirements from technological factors and improving the business analytics to meet the business needs. Many studies have validated compatibility as a significant determinant of Business Analytics adoption (Alshamaila et al., 2013; Chen et al., 2015; Wang et al., 2010; Verma and Bhattacharyya, 2017). Based on these explanations, the first hypothesis of this study is technological factor positively and significantly affects the business analytics adoption.

H2: Organizational factor positively and significantly affects the business analytics adoption

Organizational factors, such as top management support, organizational data environment, and perceived cost, have a positive influence and impact on business analytics adoption. The support from the top management team is a crucial determinant of business analytics adoption (Dubey et al., 2016; Wang et al., 2010; Gangwar, 2018). The manager has to ensure to get appropriate support from the top management team in implementing business analytics adoption. The lack of support from top management is a cause for the non-adoption of business analytics (Wang et al., 2010). Data sourcing, data mining, data accessibility, data quality, and data-driven culture in organizations are critical functions in developing a data management environment. Every function of an organization has to maximize the use and relevance of data. The organization needs to understand collaboration within the division and not keep data in silos. The challenge of these data quality and functions is supported by previous studies on business analytics adoption (Xavier et al., 2011; Mathew, 2012). According to Verma and Bhattacharyya (2017) related to perceived cost as an organizational factors dimension acts as a crucial factor in adopting business analytics. Perceived cost studies on business analytics, technology, and cloud computing adoption support perceived cost as a significant factor influencing business analytics adoption (Esteves and Curto 2013; Gangwar 2018). Based on these explanations, the second hypothesis of this study is organizational factor positively and significantly affects business analytics adoption.

H3: Environmental factor positively and significantly affects the business analytics adoption

Environment factors such as competitive pressure and industry type are the determinant for technology adoption, confirming most of the studies on analytics adoption (Chwelos et al. 2001; Gangwar 2018; Ramanathan et al. 2017). Organizations continuously monitor the technology innovations adopted by their competitors. Organizations are more likely to adopt business analytics if competing organizations are using business analytics. Furthermore, the way firms interact with direct and indirect competitors is impacting business analytics adoption. The company sees some analytical learning and communication by a competitor and starts implementing the same analytical internally. Some studies have found industry type as a significant predictor of business analytics adoption (Chwelos et al. 2001; Dutta and Bose 2015; Oliveira and Martins 2011). The adopter organizations operate with a need for a high volume of information processing to achieve their business objectives in the industries. Besides, companies tend to follow their competitor in implementing the adoption of business analytics to serve their customers by identifying and satisfying their customer's needs using business analytics adoption (Wang and Cheung 2004). The customer orientation pressure has been found to drive the adoption of business analytics in some adopter organizations. Based on these explanations, the third hypothesis of this study is environmental factor positively and significantly affects business analytics adoption.

H4: Business analytic adoption positively and significantly affects the dynamic capability

The dynamic capability model of sensing, seizing, and transforming (Teece, 2007) as a robust dimension can be affected by business analytics adoption. Besides, business analytics can give better sensing to the internal and external opportunities, i.e., detect the opportunities to improve efficiency or effectiveness in the company. Sensing the need to enhance the way business works, be more aware of internal opportunities and threats, and identify inefficiencies in existing business processes opportunities to improve efficiency or effectiveness in the company. Business analytics adoption senses the opportunities and threats in the environment better, identify opportunities for organizational change based on market conditions, be more aware of the environment, and foresees a wide range of actionable options based on its surroundings. Furthermore, business analytics adoption is a dynamic capability enabler to sense immediate problems and sales opportunities. Business analytics adoption will enhance seizing capability to develop an agreement, build consensus among relevant stakeholders, and formulate and develop a viable and effective action plan. Business analytics adoption creates a strategy to capitalize on the situation, make effective decisions about which course of action to pursue, quickly decide on the best course of action, and decide on the appropriate course of action. All of these benefits of business analytics adoption can transform and change capability, change their business processes in a timely manner, rapidly adapt their business processes to competitive changes, and quickly reallocate resources among business processes (Torres et al., 2018). Business analytics has broader implications in improving the firm's dynamic capability in enhancing value creation and competitive advantage. Aydiner et al. (2019) and Vidgen et al. (2017) try to explain how business analytics will enable a company to manage its resources by building data and skills in organizations, overcoming analytical skills shortages and technical skills shortages. The business analytics adoption will improve the process by enhancing the firm ability to produce credible analytics, manage data processes, maximize the use of data, and in the end, will improve dynamic capability. Based on the explanations above, the fourth hypothesis of this study is business analytic adoption positively and significantly affects the dynamic capability.

H5: Business analytic adoption positively and significantly affects competitive advantage

The business analytics adoption will improve competitive advantage. Vidgen et al. (2017) explain the conceptual framework for formulating a business analytics adoption for the firm to update and make a significant organizational change associated with the use of technologies that will reflect a firm's approach and capability to explore and exploit new digital technologies to improve value creation with the four basic factors. There are four dimensions of every business analytical skill strived to have: (1) Data Acquisition and Processing, (2) Descriptive analysis, (3) Predictive analysis, (4) Prescriptive analysis dimension relates to the action in response to improving business operation as well as its ability to create competitive advantage (Aydiner et al., 2019; Vidgen et al., 2017). Business Analytics adoption should exist within an organization, and the existence of these capabilities will result in the generation of organizational competitiveness. (Stevens & Johnson, 2016). The business analytics adoption of an organization can be thought of as a driver of the big data existence that the organization generates and accesses to internal and external factors. Furthermore, the impact of business analytics adoption directly to the operation, such as the supply chain, will create uniqueness and competitive advantage (Chae and Olson, 2013; Wu and Huang, 2018). The adoption of business analytics can leverage the value from data through actions based on better decisions (Vidgen et al., 2017). Business analytics adoption is not just about embracing new technology; and it can drive a change in thought and organizational behavior (Nambisan et al., 2019; Vidgen et al., 2017; Vidgen & Wang, 2006). Business analytics adoption can drive leaders, and IT teams in any enterprise to work hand in hand to meet the business requirements, have competence and capability for the new era, drive innovation, and march towards continuous improvement (Nambisan et al., 2019). This is what business analytics adoption is all about, accelerating business activities, lowering costs, improving time to market, bringing about a positive change in processes, people, and competency of the continuous improvement and the new process creation as well. With this activity and process, the business analytics adoption will induce an operational and strategic objective, in the end, will impact competitive advantage. Based on the explanations above, the fifth hypothesis of this study is business analytic adoption positively and significantly affects competitive advantage.

H6: Dynamic capability positively and significantly affects competitive advantage

The dynamic capability will affect competitive advantage through sensing, seizing, and transforming resources to create a better product and market differentiation (Akter et al., 2020; Barney, 2014). Dynamic capability in industry 4.0 is very important to catch up with the current trend of automation and data exchange. Improve and enhance competitive advantage can be prepared by assessing the dynamic capability to grab the opportunity, starting from preparation in structuring, bundling, and leveraging for the change (Helfat and Winter, 2011; Helfat & Peteraf, 2009). This change helps a company to improve its competitive advantage through structuring, bundling, and leveraging resources for process efficiency. (Sirmon et al., 2007; 2011). Dynamic capability helps an organization cope with change in the short-term and long-term vision. Management support is a motivational force for dynamic capability in affecting competitive advantage. Management support includes the institutional and adequacy of resources that should be available and adequate to improve competitive advantage. Moreover, acquiring relational or environmental resources is also needed and supports the company in improving its competitive advantage performance. Simon et al. (2007) study determines dynamic capability as a comprehensive process of structuring a firm resource portfolio, bundling resources to build capabilities, and leveraging those capabilities with the purpose of creating and maintaining value for customers and owners. Through resource management, the process view of RBT explains how VRIO resources are built, modified, and reconfigured by a dynamic capability to create a competitive advantage (Simon et al., 2007). Besides, through dynamic capability, organizational learning and environmental contingency can be accommodated to improve and impact competitive advantage (Akter et al., 2020; Oliver Schilke, 2014). Based on the explanations above, the fifth hypothesis of this study is dynamic capability positively and significantly affects competitive advantage.

3. METHODOLOGY

Sample and Data Collection Procedure

We collected the data from employees of an E-commerce company located in Indonesia. In order to examine the model, these E-commerce companies have been running for more than one year. This study eliminates an E-commerce start-up company with less than a one-year operating duration. The sample used 327 companies of E-commerce companies with highly competitive market conditions. Researchers use quantitative research designs related to the design of a research project involving 327 sample sizes and concentrate on the quality and quantity of responses to obtain answers to research questions. The researcher used the expert evaluation method for wording test with leading E-commerce managers and top management team as industry practitioners and a two-person matching profile to the respondent. These activities examine whether each questionnaire is well understood and relevant to the research context. Then, the researchers spread the questionnaires to ten or more pre-test respondents from industry practitioners. These studies use probability sampling. Sampling Criteria describe as follow: (1) The company has been established for more than one year, (2) Eliminating start-up companies that have been operated for less than one year, (3) E-commerce company include website application, mobile application, and social media commerce (4) A highly competitive and turbulence environment. In the respondent selection, the researcher chose the respondent's background as close as possible to the main study.

The questionnaire was developed based on the previous study on the literature and administrated a questionnaire-based quantitative study that has been adjusted to the research context. The researcher was also combining questionnaires to make them relevant to the research context about business analytics adoption, collaboration, and dynamic capability as the business process. Wakita et al. (2012) argue the Six Likert Scale avoided the neutral answer. The researcher used the Six Likert Scale in questionnaire development for this study. The pre-test was conducted to align the questionnaire to the real situation and problem in practice. The objective of the pre-test is to examine the reliability as well as the construct of the scales used for the latent variable indicators. The expert evaluation method was implemented for the wording test with two industry practitioners and two business analytics scholars as the representative of the respondents to examine whether each questionnaire is well understood and relevant to the research context. Then, the researchers spread the questionnaires to the ten pre-test respondents from industry practitioners. The researcher chose the respondent's background as close as possible to the main study in the respondent selection process. They are executives who conduct business analytics on a daily basis through their work, and the company was founded more than five years. Then, the researcher conducted an exploratory factor analysis by using principal component analysis (PCA) with Varimax rotation to examine whether each indicator corresponds and groups to certain categories and correctly load to certain constructs. This explanatory factor analysis was conducted after the pre-test data was completed. According to (Hair et al., 2011), the loading factors of certain indicators should be above 0. 6 for their respective constructs and lower for others. Furthermore, the researcher used Bartlett's test to examine the sample adequacy by using Kaiser-Meyer-Olkin's (KMO) measure and the usefulness of factor analysis. After that, the reliability of the constructs was estimated by using Cronbach's alpha statistics, with the result should be higher than 0.7 (Hair et al., 2011).

We invited the E-commerce company's middle to top-level management as respondents because they were positioned in the middle and top managerial and at the operational levels where they know and or experience first-hand business analytics adoption processes, collaboration, dynamic capability process to create competitive advantage through value creation. The company's human resources division provided us with a list of potential respondents. We limited the survey to the company that was considered to have strong competition. All surveys were distributed via electronic form. Respondent returned their completed surveys electronically and directly to us. In total, we received completed surveys from 131 companies. After cases with missing data had been deleted, our final sample contained 327 companies. Company average age was more than 12 years, and 50.65 percent of them were more than ten years. Concerning education, 49 percent had post-graduate degrees, 42,4 percent had bachelor's degrees, and 8.06 percent had diploma degrees or high school degrees. Respondents were dominated by males, 65.6 percent, and females, 34.4 percent. In respondent positions, 47.7 percent are top management level, 42.4 percent are in middle management, and 9.9 percent are in other positions. The company established more than 12 years (51 percent), 7-9 years (15.2 percent), 1-3 years (13.2 percent), 10-12 years (11.9 percent), 4-6 years (8.6 percent). Concerning the size of the company, 52.3 percent is a big company with more than 250 employees, 22.5 percent are medium enterprises with 50-249 employees, 13.9 small enterprises with 10-49 employees, and 11.3 percent micro-enterprises with less than ten employees. From the respective respondent, the type of E-commerce was business to customer (B2C) type 63.6 percent, business to business (B2B) type was 25.2 percent, and 11.2 percent was other types such as B2B2C, B2B, and B2C.

Measures

TOE (Technological, Organizational, and Environmental) factors

We measured TOE (Technological, Organizational, and Environmental) factors using well-established theory from Louis G. Tornatzky and Mitchell Fleischer, published in 1990. The questionnaire was adopted by Kuan and Chau (2001). For this study, the researcher used the scale items intended to measure Technological factors with complexity (TF1), IT Assets (TF2), and Compatibility (TF3). For the organizational factor, Top Management Team (OF1), Organizational Data environment (OF2), and Perceived Cost (OF3). The questionnaire for environmental factors is External Pressure (EF1) and Industry Type (EF2). The researcher created scale scores by averaging the appropriate items for each dimension after evaluating the validity of the scale items, as we elaborate on the validity evaluation.

Business Analytic Adoption

We measured business analytics adoption using a questionnaire adapted from Aydiner et al. (2019). Business analytics adoption is concerned with "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models and fact-based management to drive decision and actions." (Davenport and Harris, 2007, p.7). For the purposes of this study, the researcher used the scale items intended to measure innovativeness (DACQ), five items, Prescriptive (PRES) 5 items, Predictive (PRED) 5 items, and Descriptive (DESC). Respondent indicated their responses on a scale ranging from "strongly disagree," to "strongly agree." The researcher created scale scores by averaging the appropriate items for each dimension after evaluating the validity of the scale items, as we elaborate on the validity evaluation.

Dynamic Capability.

We measured dynamic capability using a questionnaire adapted from Kump et al. (2019). This perspective aligns and supports the context and purpose of this study, e.g., the business objectives from business analytics adoption. The business objectives of this context are not only for new products and services but also for strategic decisions and actions. Kump et al. (2019) argue the need to compare the empirical findings impairs data-based theory development from the original 14-item scale based on Teece's (2007); well-established dynamic capability framework, assessing sensing, seizing, and transforming capacities. For the purposes of this study, we used the scale items intended to measure sensing (SEN) 6 items, seizing (SEI) 5 items, and transforming (TRA) 6 items. Respondent indicated their responses on a scale ranging from "strongly disagree," to "strongly agree." The researcher created scale scores by averaging the appropriate items for each dimension after evaluating the validity of the scale items, as we elaborate on the validity evaluation.

Competitive Advantage.

We measured competitive advantage performance using innovation differentiation (IDI) 7 items and market differentiation six items. For the purposes of this study, we used the scale items intended to measure branch performance (BP) with 1 item. The researcher created scale scores by averaging the appropriate items for each dimension after evaluating the validity of the scale items, as we elaborate on the validity evaluation.

Model Estimation

This study adopted two-step structural equation modeling (SEM) to estimate the model (Anderson and Gerbing, 1988). The first step was to examine the validity and reliability of the measurement model. The examination started with evaluating the standardized factor loading (SFL) of each indicator (item). If SFL is less than 0.50, the indicator is not valid and hence must be dropped. As mentioned above, all items are included, and there is no items have dropped due to SFL less than 0.5. Similarly, the variable must be dropped if SFL is less than 0.5. There is no variable with SFL less than 0.5, so all variables are considered valid. Next, we examined the reliability of variables by testing the variance extracted (AVE) and construct reliability (CR). The dimension or variable is reliable if AVE is equal to or greater than 0.50 and CR is equal to or greater than 0.60.

The minimum sample size for SEM is five times the number of indicators modeled (Bentler and Chou, 1987). In our sample of 327 firms with 72 indicators, our sample was below the minimum requirement. Therefore, we simplified the dimensions of variables by parceling (Rhemtulla 2016) and using latent variable scoring (Joreskog, Sorbom, and Yang-Wallentin, 2006), in which the second-order confirmatory analysis model was transformed into a first-order confirmatory analysis model. Parceling decreased the number of indicators to 17 and made our sample size sufficient. It resulted in a more stable estimation of parameters for a small sample (Bandalos 2002) and improved the model's fit.

The second step of SEM was to analyze the goodness-of-fit indices (GOFIs)— Root Mean Square Error of Approximation (RMSEA), Non-Normed Fit Index (NNFI), Confirmatory Fit Index (CFI), Incremental Fit Index (IFI), Standardized Root Mean

Squared Residual (SRMR) and Goodness of Fit Index (GFI— and a significance test for path coefficients. Table 1 shows the evaluation of overall fit. Root Mean Square Error of Approximation (RMSEA) = 0.000, Normed Fit Index (NFI) = 0.940, Root Mean Square Residual (RMR) = 0.016, and Goodness of Fit Index (GFI) = 0.920. The structural model's overall fit is good. The assessment of measurement model of higher-order and lower-order constructs is shown in Table 2.

Table 1. Measurement Model Analysis

Measurement	Value	Ideal (Fit)	Remark
CMIN	89.799	small	Fit
CMIN/DF	0.863	<5	Fit
GFI	0.920	>0.90	Fit
RMSEA	0.000	< 0.05	Fit
RMR	0.016	< 0.05	Fit
PNFI	0.719	0.6 < x < 0.9	Fit
NFI	0.940	>0.90	Fit
RFI	0.922	>0.90	Fit

Table 2. Assessment of Measurement Model

Higher-Order Constructs	Composites Reliability Higher Order Construct	AVE Value of Higher-Order Construct	Lower-Order Construct		Composites Reliability Lower Order Construct	AVE Value of Lower-Order Construct
Technological Factors	0.934	0.529	Complexity	0.628	0.978	0.917
			IT Assets	0.897	0.901	0.647
			Compatibility	0.925	0.952	0.832
Organizational Factors	0.946	0.556	Top Management Supports	0.903	0.924	0.708
			Organizational Communications	0.907	0.915	0.642
			Quality of Human Resource	0.874	0.903	0.757
Environmental Factors	0.919	0.655	Competitive Pressure	0.932	0.866	0.684
			Regulatory Support	0.950	0.920	0.793
Business Analytic Adoption	0.960	0.616	Data Acquisition and Processing	0.934	0.916	0.732
			Descriptive Analytics	0.916	0.900	0.694
			Predictive Analytics	0.924	0.906	0.708
			Prescriptive Analytics	0.924	0.905	0.761
Dynamic Capability	0.971	0.665	Sensing	0.953	0.938	0.715
			Seizing	0.956	0.937	0.748
			Transforming	0.965	0.937	0.714
Competitive Advantage	0.961	0.690	Product Differentiation	0.958	0.930	0.728
			Market Differentiation	0.972	0.947	0.750

4. RESULTS AND DISCUSSION

Table 3 and Figure 1 show the results of hypothesis testing. All the seven hypotheses were empirically supported. Support for H1 shows that TF positively and significantly affects BAA. This finding is consistent with the nature of TF that triggers significant changes as it substantially modifies the way business analytics is adopted (Alshamaila et al., 2013; Chen et al., 2015; Wang et al., 2010; Gangwar, 2018). For Verma and Bhattacharyya (2017), the BAA implementation starts with gathering the business requirements from technological factors and improving the business analytics to meet the business needs. The organization must make such technological change and improvement as a response to cope with the digital era, or else the organization will lose the opportunity and the job they currently have. Besides, business analytics adoption needs to continuously upgrade technological infrastructure and software. This condition is a must-have change because they need these tools and technological upgrades to carry out and implement business analytics. The issue here is that business analytics adoption needs technological factors to improve. According to Kuan and Chau (2001), the technological factor is also perceived as direct benefits and perceived as indirect benefits. So, the technology should relate to the creation of a product, service, or market differentiation. Secondly, technological factors should perceive as relatively not difficult to understand and use. This finding enlightens us that, as a technological factor improves, BAA will be adopted effectively.

Support for H2 demonstrates the positive and significant effect OF has on BAA. OF, such as devoting time from top management to the business analytics program in proportion to its cost and potential, reviewing plans, following up on results, and facilitating the management problems involved with integrating information and communication technology (ICT). Managing data resources enhances the effective adoption of business analytics in an organization (Ramamurthy et al.,2008). Besides, TF and OF are internal factors within an organization. Hence the company needs to effectively use these resources. Without complementary internal incentives such as adequate analytical data understanding, TF and OF cannot be extensively capitalized on. As a result, firms could not sufficiently predict the future and plan ahead. Conversely, TF and OF are enhanced to maximize BAA's data-driven forecasting capabilities. Which uses descriptive, predictive, and prescriptive analytics to make better decisions, gain insight, and drive action that is reliant on strong resources such as TF and OF. This is reflected by the positive and significant relationship observed in the results of this study. Besides, TF and OF are internal factors within an organization, hence the inability to effectively use these resources. Without complementary internal incentives such as adequate analytical data understanding, TF and OF cannot be extensively capitalized on. As a result, firms could not sufficiently predict the future and plan. This is reflected by the positive and significant relationship between OF and BAA, which is observed in the results of this study.

The last resource in the TOE framework is the environment which significantly and positively influences the BAA. Influences from the external business environment make the company possible to foster BAA by gathering data and information from outside the company. The competitive pressures from the external environment that influence the company will enhance the adoption of business analytics. The impact of competitors and government policy or regulation in which its business operates other external factors that influence BAA significantly. Support for H3, this study found that EF positively and significantly affects BAA. Nevertheless, these conditions happen because of BAA's inherent reactive nature, which makes it more suitable to address external factors such as rapidly changing environments (Teece, 2007). Support for H4 shows that BAA positively and significantly affects the dynamic Capability. BAA contributes to dynamic capability towards the processes of descriptive, predictive, and prescriptive to sense, seize, and transform in ambiguity and uncertainty conditions. BAA enhances the sensing, coordinating, learning, integrating, and reconfiguring process, ultimately leading to enhanced competitiveness levels. The dynamic capabilities perspective helps to shed light on how to employ big data analytics to detect, anticipate and respond to an uncertain environment.

Supports for H5 and H6 are consistent with Stevens and Johnson (2016) and Vidgen et al. (2017), who found a positive and significant relationship between Business analytics and performance. BAA improves a firm's effectiveness inside and outside an organization so they can work more productive, effective, and successful. In the end, BAA significantly and positively enhances and influences a firm's competitive advantage with the product, services, and market differentiation. Dynamic Capability can also influence and positively impact competitive advantage by making firms adapt faster to new conditions under uncertainty than their competitors. This condition increases efficiency, identifies new business opportunities, and creates CA directly. In addition, this study found that both BAA and dynamic capability positively and significantly affect CA, with BAA having a much higher impact than dynamic capability. BAA is able to create a larger degree of CA as it mediates the maximization of TF and OF. Moreover, BAA relies on analytical data in addition to business understanding which enables the forecasting and automation of future strategic decisions. The maximization of resources and future insight, which dynamic capability is incapable of doing to a competitive degree. Conclusively, the game-changing adoption of business analytics over the dynamic Capability serves a much more strategic role for firms in achieving competitive advantage.

Table 3. Results of Hypothesis Testing

	Estimates	T Statistics	P Values	Remark
Technological-> Business Analytics Adoption	0.34	***	<0.001	Supported
Organizational-> Business Analytics Adoption	0.59	0.01	<0.05	Supported
Environmental -> Business Analytics Adoption	0.28	0.08	<0.10	Supported
Business Analytics Adoption->Dynamic Capability	0.93	***	<0.001	Supported
Business Analytics Adoption->Competitive Advantage	0.36	0.008	<0.010	Supported
Dynamic Capability->Competitive Advantage	0.48	0.002	<0.010	Supported

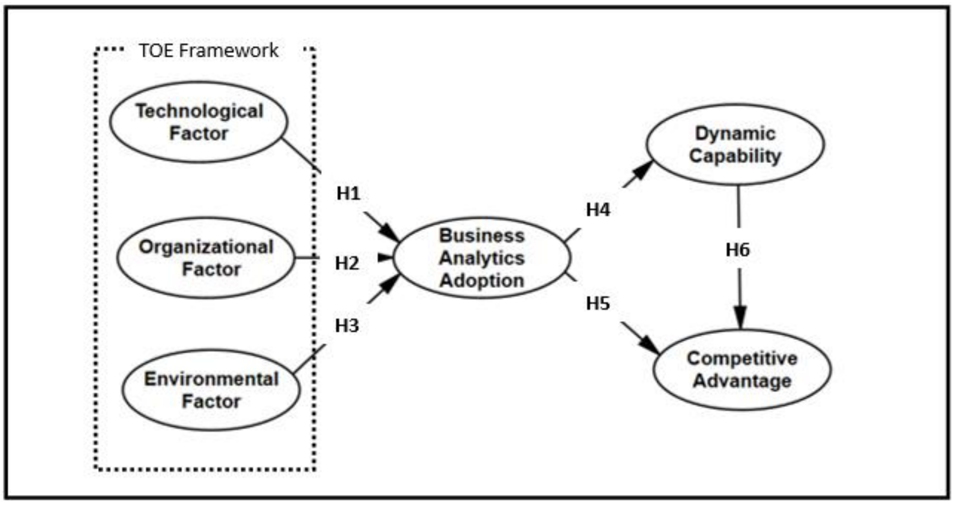

Figure 1. Structural Model

These findings highlight the importance of the TOE framework that BAA mediates to create a competitive advantage. Besides, this study shows BAA mediated Technological and organizational factors to dynamic capability from the results of the Sobel Test calculation of Technological factors as follows. The z-value is 2.317, with a standard error of 0.134 and a p-value of 0.02049952. The z-value obtained is 2.317 > 1.96, and the p-value is 0.02049952 < 0.05, proving that BAA is able to mediate the relationship between TF and dynamic capability. The mediating role of BAA proved significant. The Sobel test calculation of Organizational factors shows the z-value is 4,627 with a standard error of 0.118 and a p-value of 0.02049952. The z-value obtained is 2.317 > 1.96, and the p-value is 0.0000037 < 0.05, thus proving that BAA is able to mediate the relationship between OF and dynamic capability. Nevertheless, BAA proved to be insignificant in mediating environmental factors to dynamic capability. From the results of the Sobel Test calculation, the z-value is 1.725 with a standard error of 0.150 and a p-value of 0.08444977. The z-value obtained is 1.725 < 1.96, and the p-value is 0.08444977 > 0.05, thus proving that BAA does not mediate the relationship between EF and dynamic capability.

Other important results from this study related to previous literature, this study suggests that TF, OF, and EF are more directly related to BAA than to dynamic capability. Additionally, we can see the connection for H3 to support BAA is the lowest factor compared to TF and OF. As seen in Table 3 and Figure 1, the coefficient for H3 is 0.28, and the lowest coefficient is compared to H1 (0,34) and H2 (0,59). So, among each factor in TOE framework, the organizational factor has the highest impact on BAA, followed by the technological factor, as we can see from the result that all toe factors significantly and positively support BAA as an integrated framework. Although all TOE factors influence and enhance BAA, a company should focus on organizational factors, technological factors, and environmental factors, respectively. The direct impact of BAA on DC (0,93) is higher than on CA (0,35) directly. Dynamic capability is important in mediating BAA to achieve CA. From the results of the Sobel Test calculation, the z-value is 2.914 with a standard error of 0.153 and a p-value of 0.00356119. The z-value obtained is 2.914 > 1.96, and the p-value is 0.00356119 < 0.05, thus proving that DC is able to mediate the relationship between BAA and CA. The mediating role of DC proved significant. The mediated of DC is an important role of BAA in achieving CA. Even BAA and CA has direct correlation, BAA mediated by DC to CA are higher influence (0,93 x 0,48) than the indirect one (0.35 versus 0.93 x 0.48 = 0.446), meaning to impact CA, BAA better mediated by DC. The crucial role of BAA is to support DC, and the more powerful role of DC is to utilize the use of BAA in achieving CA. In conclusion, CA can rely on the strategic role of DC, and DC can be enhanced through the BAA as a game-changer in this digital era by creating a product, services, and market differentiation using the extensive use of data.

5. CONCLUSION

Based on the discussions above and to answer the research question, we can conclude that technological, organizational, and environmental factor can impact competitive advantage indirectly through business analytics adoption and dynamic capability. TOE framework can increase business analytics adoption in relation to enhancing the effect on dynamic capability and competitive advantage. Business analytics adoption can, directly and indirectly, improve competitive advantage. Business analytics adoption relays to dynamic capability (0.93 x 0.48 = 0.446) to achieve competitive advantage is better than business analytics adoption directly to competitive advantage (0.35). Business analytics adoption and dynamic capability play an important role in achieving competitive advantage. Essentially, we have two paths to achieve competitive advantage through business analytics adoption and dynamic capability. Business analytics adoption can directly impact competitive advantage, and business analytics adoption can also relay to dynamic capability to impact competitive advantage. From the results of the Sobel Test calculation above, the z-value obtained is 2.914 > 1.96, and the p-value is 0.00356119 < 0.05, thus proving that dynamic capability is able to mediate the relationship between business analytics adoption and competitive advantage. Without considering errors, business analytics adoption directly impacts competitive advantage has a lower coefficient score than business analytics adoption mediated by dynamic capability to impact competitive advantage. From the study above, business analytics adoption and dynamic capability play a more important role as mediated for TF, OF, and EF to impact competitive advantage. From the Sobel test calculation, we can conclude business analytics adoption mediated the relationship between TF and OF, but business analytics adoption proved to be insignificant in mediating environmental factors to dynamic capabiltiy. The adoption of business analytics needs TF, OF, and EF as the internal and external resources to enhance the business analytics adoption and dynamic capabiltiy in achieving competitive advantage. In the digital era, organizations need technologies to transform data, people's skills and ideas to be applied to improve products, processes, and procedures. Technology improves the adoption of business analytics, and in the end, these resources and processes create better product differentiation and market differentiation. To enhance business analytics adoption in achieving competitive advantage, technological, organizational, and environmental factor are significant resources. Besides, business analytics adoption can be improved through the dimensions within the business analytics adoption itself, namely increasing data acquisition and processing capabilities and descriptive, predictive, and prescriptive analytic capabilities within the company. These improvements are mostly concerned with achieving the firm's competitive advantage.

Besides technological factors, organizational factors, such as the top management's support of adopting and implementing business analytics, influence the opportunities for improved competitive dynamic capability and the firm's competitive advantage performance. This finding reminds organizations to adopt and implement business analytics to gain a firm's dynamic capability and competitive advantage. This study was framed and proved that technological-organizational-environmental factors such as the TOE framework influences business analytics adoption. Although such a frame was developed based on an in-depth literature review, this study can empirically demonstrate causal-effect relations shown in Figure 1 with cross-sectional data, and, therefore, we propose future studies will investigate the robustness of the TOE framework, is it really a solid framework that should be integrated as a factor or not. The next study can also be conducted with more samples in a longitudinal manner.

Furthermore, the model shown in Figure 1 has not considered knowledge retention and internal collaboration within the firm, such as avoiding silos sharing resources and information between divisions. The organization needs to understand internal collaboration within the division and not keep data in silos. Knowledge retention and collaboration, for example, can mediate the relationship between business analytics adoption and dynamic capability in achieving competitive advantage. In contrast, an external collaboration between a firm in the same industry may moderate the relationship between business analytics adoption and dynamic capability. So, future studies should include those factors or others in the research model. This study was conducted in an E-commerce company with specific characteristics that make the generalization of its findings problematic. Therefore, we suggest future studies be taken on other companies with different characteristics from the E-commerce company. Such companies could be a more traditional company that has also experienced business analytics adoption signified by the existence of technology and that has long been practicing business analytics adoption, as well as a manufacturing company that has adopted business analytics to make its operations more effective and achieve a competitive advantage to win a stiff competition in the industry.

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