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BIG DATA ANALYTICS ADOPTION AND FIRMS' PERFORMANCE IN VIETNAMESE SMES

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Abstract

Big Data Analytics (BDA) adoption represents a transformative phenomenon in contemporary industry, offering capabilities for precise decision-making and enhanced operational efficiency. However, the factors influencing its adoption and the resultant impacts on small and medium enterprises (SMEs) remain insufficiently understood, motivating the focus of this study. Analyzing data from 388 Vietnamese SMEs in manufacturing, we identify several critical determinants of BDA adoption. The study underscores the substantial positive impact of BDA adoption on both the marketing and financial performance of SMEs. Insights into the drivers of BDA adoption gleaned from this study provide SME managers with actionable knowledge to implement strategic initiatives conducive to effective BDA integration. Thus, this research contributes to a clearer understanding of BDA adoption dynamics in SMEs, facilitating informed decision-making by managers and strategic planning by service providers in this evolving technological landscape.

Key Words: *Big Data, SME, Big Data Analytics Adoption*

1. Introduction

In recent years, Vietnam witnesses a significant impact of big data on its business environment, profoundly influencing various sectors. Big data, characterized by its volume, velocity, and variety, has empowered Vietnamese businesses to make informed decisions quickly and efficiently. For example, according to Vietnam's Ministry of Information and Communications report (2023), companies utilizing big data analytics have achieved up to 30% higher operational efficiency and shortened their time-to-market for new products by 20%. This technological shift has not only improved decision-making processes but also facilitated targeted marketing, customer segmentation, and predictive analytics, providing competitive advantages in both local and global markets. As Vietnam continues to embrace digital transformation, the incorporation of big data is expected to further revolutionize business operations, driving innovation and economic expansion across various industries.

Big data analytics (BDA), in general, has profoundly reshaped competitive dynamics in business operations (Müller, Fay, & vom Brocke, 2018). It introduces advanced methodologies to uncover concealed patterns within vast datasets, enabling informed decision-making, heightened productivity, knowledge generation, and innovation enhancement (Acharya, Singh, Pereira, & Singh, 2018; de Vasconcelos & Rocha, 2019; Yaqoob et al., 2016). Broadly, big data encompasses records of interactions involving employees and customers archived within organizational systems (Calvard & Jeske, 2018; Shirdastian, Laroche, & Richard, 2019), yielding actionable insights categorized as descriptive, predictive, and prescriptive outcomes (Lamba & Dubey, 2015, p. 5). Defined by its characteristics of volume, velocity, and variety - encompassing both structured and unstructured data - extracting valuable knowledge from big data remains a multifaceted endeavor (Calvard & Jeske, 2018).

Literature indicates that BDA adoption empowers firms to enhance operational efficiencies and leverage strategic advantages (Ghasemaghaei, 2018; Mikalef, Boura, Lekakos, & Krogstie, 2019; Mikalef, Krogstie, Pappas, & Pavlou, 2019; Nam, Lee, & Lee, 2019; Raguseo, 2018; Raguseo & Vitari, 2018). Consequently, many large enterprises have integrated BDA into diverse functions, including market trend forecasting and customer behavior analysis, to identify opportunities for refinement (Mandal, 2018). However, despite the pivotal role of small to medium-sized enterprises (SMEs) in national economies, their adoption of BDA lags significantly behind, primarily due to limited resources and understanding of big data applications (Christina & Stephen, 2017; Coleman et al., 2016; Sen, Ozturk, & Vayvay, 2016; Shin, 2016).

Research reveals a paucity of studies exploring the factors influencing BDA adoption among SMEs (Maroufkhani et al., 2019). Addressing this gap, this study applies the technological - organizational - environmental (TOE) model to investigate these adoption drivers. The TOE model is noted for its adaptable framework in elucidating technology adoption levels across organizations (Grant & Yeo, 2018; Tsou & Hsu, 2015).

Despite research extensively examining the impacts of TOE factors on the adoption of various technologies (Chandra & Kumar, 2018; Hsu & Lin, 2016), applying these findings to the adoption of BDA by Small and Medium-sized Enterprises (SMEs) necessitates caution due to the nuanced influences of TOE factors, which vary based on technology type, firm size, and geographical context (Alharbi, Atkins, & Stanier, 2016; Ghobakhloo, Arias-Aranda, & Benitez-Amado, 2011; Wang, Jin, & Mao, 2019). Each technology possesses distinct characteristics, and the factors influencing successful adoption differ accordingly (Wang et al., 2019). Gangwar, Date, and Raoot (2014) highlighted these variations by observing that factors like compatibility significantly drive adoption in technologies such as knowledge management and radio frequency identification (RFID) but show less impact on others like enterprise resource planning (ERP) and electronic data interchange (EDI).

Moreover, the applicability of TOE factors varies between large firms and SMEs due to disparities in resource availability, organizational structure, technological infrastructure, and environmental conditions (Ghobakhloo, Arias-Aranda et al., 2011; Themistocleous et al., 2005). These differences underscore the need for a tailored model to comprehend the drivers of BDA adoption among SMEs. Alharbi et al. (2016) emphasized that national requirements and environmental contexts significantly influence how TOE factors affect technology adoption levels, necessitating a case-specific approach.

While BDA investments hold potential to enhance performance, studies predominantly focus on their impact within large corporations, leaving a notable gap in empirical research on SMEs (Raut et al., 2019; Wamba et al., 2017; Wang, Kung, Wang, & Cegielski, 2018). In this paper, we attempt to formally address the mentioned research gap by following two main questions: 1) What technological, organizational and environmental factors influence the extent of BDA adoption among Vietnamese SMEs? and 2) Does BDA adoption influence SMEs' performance?

With this paper, we contribute to the existing body of knowledge by providing insights into both the antecedents and outcomes of BDA adoption among SMEs within a unified framework, which serves as a model for BDA adoption of SMEs, in the contexts of a developing country - Vietnam. The findings aim to further assist SME managers and owners in understanding the critical factors involved in successfully adopting BDA. Additionally, policymakers can leverage these insights to formulate strategies that promote BDA adoption among SMEs effectively.

2. Literature Review

The rapid evolution of digital technologies, including social networking platforms, advanced mobile technologies, e-commerce websites, and search engines, has precipitated a significant increase in the volume of data known as big data (Surbakti, Wang, Indulska, & Sadiq, 2020). Big data is characterized by three primary attributes, commonly known as the three Vs: Volume, Variety, and Velocity (Russom, 2011). Volume refers to the sheer magnitude of data collected, which enables firms to uncover hidden insights and patterns critical for gaining actionable knowledge (Ghasemaghaei, 2020). Variety encompasses the diverse formats of data, including unstructured, semi-structured, and structured data, posing challenges to traditional analytic systems in terms of management and analysis (Mohapatra & Mohanty, 2020). Velocity denotes the speed at which data is generated, processed, and analyzed in real-time, necessitating agile analytical capabilities (Jeffrey Kuo, Lin, & Lee, 2018; Shukla, Yadav, Kumar, & Muhuri, 2020).

The terminology surrounding big data, Big Data Analytics (BDA), and BDA capabilities (BDAC) varies among researchers, albeit with a degree of interchangeability (Mikalef, Pappas, Krogstie, & Giannakos, 2018). Some definitions focus solely on the data and its inherent characteristics, while others emphasize the analytics process, encompassing the tools and techniques essential for deriving meaningful insights (Mikalef et al., 2018). BDAC emerges when the discussion shifts to the transformative impact of analytical techniques in uncovering hidden values within big data (Dubey, Gunasekaran, & Childe Stephen, 2019). The challenges posed by big data's attributes - volume, velocity, and variety - require organizations to adopt sophisticated BDA practices such as data mining, visualization, and sense-making to derive actionable intelligence (Grossman & Siegel, 2014). Successful utilization of big data hinges on organizational capabilities such as a data-driven culture and effective organizational learning mechanisms (Mikalef et al., 2018). Hence, the concept of BDAC has gained prominence, as it encompasses the organizational readiness and capabilities necessary to effectively implement big data initiatives and derive strategic business value from them.

BDA has emerged as a transformative force capable of significantly enhancing the operational efficiency and strategic

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effectiveness of firms (Ji-fan Ren, Wamba, Akter, Dubey, & Childe, 2017; Wamba et al., 2017). By leveraging advanced data processing techniques, organizations can convert raw data into actionable intelligence and meaningful insights, thereby improving overall performance (Chen, Preston, & Swink, 2015; Maroufkhani et al., 2019). This capability is particularly crucial in enhancing organizational agility, as BDA facilitates quicker processing speeds and more efficient task completion (Ghasemaghaei, Hassanein, & Turel, 2015). Nevertheless, challenges persist regarding the realization of business value from BDA investments, often due to insufficient availability or quality of data necessary for meaningful analysis (Ji-fan Ren et al., 2017).

To evaluate the impact of BDA comprehensively, Wamba et al. (2017) advocate for employing the Resource-Based View (RBV) theory, which elucidates how organizational resources and capabilities, including those for innovation, influence firm performance (Barney, 2014; Ji-fan Ren et al., 2017). The influence of BDA extends across various industries, each harnessing its capabilities differently to enhance performance. In retail, for example, BDA is instrumental in developing customer management strategies (Wamba et al., 2017). Similarly, in healthcare, BDA aids in making more precise medical decisions, thereby enhancing overall business value (Rajabion et al., 2019; Wang et al., 2018). In manufacturing and supply chain management, BDA contributes to sustaining firm performance by optimizing processes and improving decision-making (Raut et al., 2019; Rehman et al., 2016; Gunasekaran et al., 2017; Mandal, 2018). Studies examining the adoption of BDA consistently highlight its potential to impact financial and overall firm performance positively (Akter et al., 2016; Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015; Wamba et al., 2017).

The subsequent section delves into the theoretical foundations underpinning this study, emphasizing the theoretical frameworks that guide the exploration of BDA's effects on organizational performance.

3. Model & Hypotheses Development

Theoretical underpinnings for this study include the Technology-Organization-Environment (TOE) model, the Diffusion of Innovation theory (DOI), and the Resource-Based View (RBV). Central to the study is the RBV theory, which frames BDA adoption as a capability within firms and views it as an intangible resource. According to Galetsi, Katsaliaki, and Kumar (2020), acquiring new knowledge and skills enhances a firm's technological capabilities, particularly its capacity for BDAC, thereby improving overall performance. Gupta and George (2016) assert that organizational resources are pivotal in developing BDAC, emphasizing that these resources enable firms to effectively collect and utilize data for informed decision-making.

Dubey et al. (2019) suggest that BDAC functions as a facilitator within organizations, encompassing the tools, techniques, and processes necessary for data processing and analysis, ultimately enhancing operational decision-making. Mikalef, Krogstie et al. (2019) and Gupta and George (2016) categorize organizational resources required to build BDAC into tangible assets such as data and technology, and intangible assets such as organizational learning and a data-driven culture. Intangible resources, according to Mikalef, Krogstie et al. (2019), play a crucial role in expanding decision-makers' perspectives and enhancing their knowledge for sound decision-making.

The information derived through BDAC, as highlighted by Dubey et al. (2019), provides real-time insights that enable organizations to perform more effectively (Gupta and George, 2016; Wamba et al., 2017; Akter et al., 2016). Building on previous research, this study considers BDAC holistically as an intangible resource critical for successful innovation adoption within firms. BDAC, therefore, acts as a catalyst for shaping organizational culture and promoting the strategic use of big data to improve operations, enhance decision-making processes, and sustain competitive advantage and firm development (Kwon, Kwak, & Kim, 2015; Wang & Hajli, 2017).

Researchers such as Piaralal, Nair, Yahya, & Karim (2015) and Alshamaila, Papagiannidis, & Li (2013) have underscored the integration of the TOE model with the DOI theory as particularly suited for understanding technology adoption within SMEs. DOI theory emphasizes the role of technological characteristics in driving the diffusion and adoption of innovations throughout an organization (Chiu, Chen, & Chen, 2017). In contrast, the TOE model comprehensively considers both internal and external factors that influence technology adoption across firms, with a particular focus on organizational and environmental contexts (Chiu et al., 2017; Zhu, Kraemer, & Xu, 2006).

Kapoor, Yogesh, and Michael (2014) highlight the importance of considering technological implementation aspects in studies of innovation adoption. Integrating the technological factors emphasized by DOI theory into the broader framework of the TOE model can provide a robust theoretical foundation for examining technology adoption, thereby enhancing the explanatory power of Rogers' DOI theory in understanding intra-firm innovation diffusion (Hsu, Kraemer, & Dunkle, 2006).

Building on the evolving literature on BDA and its business implications, as well as the TOE factors influencing technology adoption, this study proposes a conceptual model integrating the TOE model with DOI and RBV theories. This framework explores a spectrum of TOE factors including technological aspects (such as relative advantage, compatibility, complexity, trialability, and observability), organizational factors (such as top management support and organizational readiness), and environmental factors (including competitive pressure, external support from vendors, and government regulations). The subsequent sections of this study articulate the rationale behind the proposed hypotheses, aiming to provide insights into the factors driving BDA adoption among SMEs.

3.1. Technological Context

H1: The relative advantages of BDA impact SMEs' BDA adoption.

The technological context encompasses both endogenous and exogenous elements crucial for understanding technology adoption. One pivotal element is relative advantage, defined as the perceived improvement a new technology offers over existing ones (Baker, 2012; Kapoor, Dwivedi, & Williams, 2015). Organizations are significantly influenced by the perceived benefits that a technology, such as BDA, can bring to their specific operational performance (Gu, Cao, & Duan, 2012). Relative advantage assesses whether adopting BDA provides greater benefits compared to current technologies employed in business operations (Rogers, 2003). Studies by Ghobakhloo, Arias-Aranda et al. (2011) and Ullah and Qureshi (2019) indicate that SMEs are more inclined to adopt technologies if they perceive the advantages outweigh those of their current systems.

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H2: Compatibility impacts SMEs' BDA adoption.
Another critical aspect in the technological context is compatibility, which examines the alignment of a new system with existing organizational systems and practices (Chen et al., 2015; Kapoor, Dwivedi, & Williams, 2014). Compatibility reflects how seamlessly a technology can integrate with the culture and operational workflows of an organization (Verma & Bhattacharyya, 2017; Gangwar, 2018). Empirical studies by Verma and Bhattacharyya (2017), Chen et al. (2015), and Gangwar (2018) underscore compatibility as a significant driver for BDA adoption. Firms can enhance compatibility by adjusting policies and procedures to accommodate new technologies effectively (Gangwar, 2018).

H3: Perceived complexity of BDA impacts SMEs' BDA adoption.
Rogers (2003) highlighted that the adoption of new technologies often falters when perceived as overly ambitious or challenging to implement. Challenges arise particularly in reconfiguring organizational processes, underscoring the importance of user-friendly technologies to facilitate adoption (Alshamaila et al., 2013; Kandil et al., 2018). As technologies become more sophisticated, the complexity and uncertainty surrounding their adoption increase, posing significant barriers (Harindranath et al., 2008; Kandil et al., 2018). Decision-makers are consequently hesitant to adopt innovations perceived as complex (Asiaei, 2019; Ghobakhloo, Arias-Aranda et al., 2011). Complexity has consistently shown a negative correlation with technology adoption, including within the realm of BDA, where complexities associated with managing large volumes of diverse data negatively impact adoption rates (Gangwar, 2018; Lai et al., 2018). Thus, SMEs are less inclined to adopt innovations perceived as requiring excessive effort.

H4: Perceived uncertainty and insecurity impact SMEs' BDA adoption.
Uncertainty, as defined by Alshamaila et al. (2013), represents the risks accompanying the adoption and integration of new technologies within organizational systems. Security and privacy concerns are prominent uncertainties hindering the adoption of data-related innovations (Asiaei, 2019; Aziz, 2010). Cloud computing, integral to many data innovations, is particularly sensitive to uncertainty regarding data security and privacy (Alshamaila et al., 2013). Recent literature underscores the critical role of addressing security concerns in facilitating BDA adoption (Ghasemaghaei, 2020; Raguseo, 2018; Sun et al., 2018). Security concerns are magnified in the context of outsourcing, where firms rely on third-party tools or cloud services for BDA solutions, potentially compromising data control (Asiaei, 2019; Priyadarshinee et al., 2017). In pursuit of leveraging big data benefits, firms often opt to outsource due to limitations in internal capabilities and the novelty of big data technologies (Wood, 2013). However, outsourcing introduces security and privacy risks associated with relinquishing data control to external entities. This study posits that uncertainties and security concerns significantly influence BDA adoption.

H5: Trialability impacts SMEs' BDA adoption.
Trialability, as defined by Laurell et al. (2019), pertains to the extent to which an IT innovation can be experimented with before full-scale adoption. This attribute is crucial for early adopters, particularly SMEs, as it allows them to assess the innovation's effectiveness early on and reduce uncertainty (Alshamaila et al., 2013; Moghavvemi et al., 2012; Ramdani & Kawalek, 2007). Rogers (2003) posited that the ability to trial an innovation accelerates its adoption rate, a sentiment echoed by Wu and Corbett (2019) who emphasized that early exposure facilitates faster adoption. Studies by Jeyaraj et al. (2006) and Asare (2016) underscored trialability as a critical precursor to the adoption of internet and online technologies among academics. In the context of BDA, SMEs stand to benefit from the ability to trial the technology, potentially increasing their propensity to adopt and integrate BDA innovations into their operations.

H6: Observability impacts SMEs' BDA adoption.
Observability, according to Rogers (2003), refers to the visibility of innovation's outcomes to others. While observability has been found to promote adoption within firms (Kapoor, Yogesh et al., 2014), its impact on the adoption of IT techniques in SMEs has been debated, with some studies suggesting no significant positive effect (Ramdani & Kawalek, 2007). Despite this controversy, this study argues that if the benefits and outcomes of BDA adoption are observable to SME owners, they are more likely to perceive its value and consequently adopt BDA in their businesses.

3.2. Organizational Context

H7: The support of top managers impacts SMEs' BDA adoption.
Management support and organizational readiness are pivotal factors examined in this study that influence the adoption of BDA by SMEs. Top management support refers to the extent to which senior managers grasp and endorse the technological capabilities of new systems like BDA (Sanders, 2008). Jahanshahi and Brem (2017) emphasized that decision-makers within SMEs, often part of the top management team, play a crucial role in driving innovation adoption. Their support serves as a bridge between individual readiness and organizational adoption, influenced significantly by the innovativeness of top leaders (Chen et al., 2015; Cruz-Jesus et al., 2019; Alshamaila et al., 2013). Studies have consistently highlighted that without robust support from top management, SMEs may hesitate to adopt new technologies, potentially hindering innovation initiatives (Asiaei, 2019; Ramdani & Kawalek, 2007, 2008).

H8: Organizational readiness impacts SMEs' BDA adoption.
Organizational readiness pertains to a firm's preparedness and capability to adopt new technologies, encompassing technical expertise and investment capacity (Taxman et al., 2014; Yoon & George, 2013). In the domain of business analytics and big data, scholars argue that organizational readiness is a prerequisite for successful BDA implementation (Gangwar, 2018; Ramanathan et al., 2017). Studies specific to SMEs by Asiaei (2019) and Ghobakhloo, Arias-Aranda et al. (2011) affirm that organizational readiness significantly and positively correlates with the adoption of new technologies. Therefore, this study asserts that organizational readiness represents a critical precondition for BDA adoption in SMEs.

3.3. Environmental Context

Environmental factors encompass external elements that organizations encounter beyond their boundaries (Xu, Ou, & Fan, 2017). Within this context, businesses are particularly sensitive to the dynamic external ecosystem. According to the TOE model, competitive pressures, external support, and governmental regulations are critical external factors influencing the adoption of BDA among SMEs.

H9: Competitive pressure impacts SMEs' BDA adoption.

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Competitive pressure, as defined by Chen et al. (2015, p. 18), refers to external influences prompting organizations to utilize BDA, stemming from customers, suppliers, and competitors. Studies by Ghobakhloo, Arias-Aranda, et al. (2011) and Asiaei (2019) highlight that SMEs facing heightened competitive pressures tend to adopt new technologies more successfully. Grandon and Pearson's (2004) research indicated that competition significantly impacts technology adoption in SMEs, aligning with findings by Aboelmaged (2018) that environmental pressures from media, competitors, and customers significantly influence business practices. Moreover, the increasing adoption of BDA by competitors motivates SME owners and managers to embrace business intelligence and analytics to enhance competitive positioning (Chen et al., 2015; Lautenbach, Johnston, & Adeniran-Ogundipe, 2017).

H10: External support impacts SMEs' BDA adoption.

External support, in the context of this study, refers to the assistance provided by vendors or third-party entities to facilitate innovation adoption within firms (Biney, 2019; Gangwar, 2018). It serves as a critical driver for successful innovation adoption, exerting a positive influence on firms' readiness to adopt new technologies (Ghobakhloo, Arias-Aranda et al., 2011; Ren, Ngai, & Cho, 2010). For firms adopting BDA, external support from vendors plays a substantial role by enabling them to enhance their innovation capabilities through access to vendor expertise and open-source platforms (Gangwar, 2018). Particularly for SMEs lacking sufficient internal technical resources, leveraging external platforms and training programs can significantly bolster their readiness to adopt innovations like BDA.

H11: Government regulation impacts SMEs' BDA adoption.

Government regulation encompasses policies, incentives, and regulatory frameworks that can either promote or restrict the adoption of specific technologies within firms (Stieninger & Nedbal, 2014; Tornatzky, Fleischer, & Chakrabarti, 1990). Lai et al. (2018) underscored that government regulations, through promotion initiatives, technological standards, and legislative measures, can effectively influence the adoption of BDA among firms. Studies by Hsu, Ray, and Li-Hsieh (2014) and Lai et al. (2018) further support this assertion, demonstrating that firms facing stringent regulatory environments are more inclined to adopt technologies such as cloud computing. In the context of BDA adoption, recent literature highlights the role of government regulations in providing incentives and support mechanisms that stimulate firms' willingness to adopt new data technologies.

3.4. BDA Adoption & Performance

H12: SMEs' BDA adoption impacts SMEs' financial performance.

Previous research has consistently demonstrated that BDA significantly enhances financial performance within organizations (Akter et al., 2016; Wamba et al., 2017). BDA techniques are shown to improve return on investment (Akter et al., 2016) and streamline processes such as e-commerce transactions, ultimately boosting sales and revenue (Jayanand et al., 2015). According to Hofmann (2017), the deployment of BDA solutions yields robust financial outcomes, with Raguseo and Vitari (2018) specifically identifying a positive correlation between BDA implementation and improved financial performance, even amid market turbulence and environmental variability, attributing this to enhanced customer satisfaction, loyalty, and profitability. Despite the potentially high costs associated with BDA adoption, investments aimed at enhancing BDA assets and capabilities are linked to significant gains in organizational productivity (Müller et al., 2018). Yang, See-To, and Papagiannidis (2020) emphasize that the predictive capabilities of BDA enable organizations to develop business models that generate increased revenues. Building on this body of knowledge, Ji-fan Ren et al. (2017), Raguseo and Vitari (2018), and Wamba et al. (2017) have all underscored the positive impact of BDA adoption on enhancing financial performance. Yasmin et al. (2020) further elaborate that BDA tends to exert a more pronounced influence on improving financial performance compared to market performance. In accordance with these findings, we hypothesize that SMEs engaging in BDA adoption will experience elevated levels of financial performance.

H13: SMEs' BDA adoption impacts SMEs' market performance.

BDA applications empower organizations to effectively harness the latent value of extensive data sets, enhancing decision-making and fostering innovation (Baesens et al., 2016). Furthermore, BDA plays a pivotal role in refining marketing strategies by leveraging customer engagements, thereby bolstering overall market performance (Saldanha et al., 2017). Market performance, characterized by the ability to expand market share, swiftly penetrate new markets, and successfully introduce new products and services, underscores the transformative impact of BDA in contemporary business contexts (Vitari & Raguseo, 2019). Dong and Yang (2020) emphasize that BDA contributes significantly to firms' value creation and market performance by facilitating informed decisions in innovation and marketing strategies. The adoption of BDA enhances a firm's dynamic capabilities, enabling proactive identification of market opportunities and risks, facilitating rapid market penetration, and improving product and service innovation (Côrte-Real et al., 2017; Davenport, 2014; Shirazi & Mohammadi, 2019). This utilization of organizational resources like BDA reinforces competitive advantages and subsequently enhances marketing performance (Raguseo & Vitari, 2018). As firms bolster their competitive edge, they can enhance market performance through increased market share, market development, and sales growth (Chakphet et al., 2020). BDA's advanced analytical solutions enable firms to swiftly identify market opportunities and threats, thereby refining market strategies, products, and services (Vitari & Raguseo, 2019).

4. Methodology

4.1. Measurements

We adapted, compiled, and utilized previously validated survey questionnaires to gather data for this study. The measurement items can be found by following their respective sources listed in Table 1 below. Building on prior research arguments (Dwivedi et al., 2013; Shareef et al., 2017; Sharma & Sharma, 2019), we employed a five-point Likert-type scale ranging from 1 ('strongly disagree') to 5 ('strongly agree') for most constructs, except for market performance and financial performance, which were measured on a scale ranging from 1 ('much worse than major competitors') to 5 ('much better than major competitors'). To ensure the questionnaire's reliability and clarity, a preliminary version was pretested by three academic experts and two industry professionals specializing in BDA. Based on their feedback, the questionnaire underwent revisions before being used in the pilot study. Given that the research is conducted in Vietnam, the instrument was translated into Vietnamese by the authors and a group of professional translators and validated by SME experts in Vietnam. A back-to-back translation process ensured the consistency and accuracy of each item's meaning. Prior to data collection from the

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larger population, the translated questionnaire underwent a pilot test involving 40 SMEs' representatives to assess survey comprehensibility and to evaluate the constructs' reliability (Dwivedi et al., 2013; Kapoor et al., 2014). The Cronbach's alpha coefficients for all constructs exceeded 0.7, indicating satisfactory reliability (Hair et al., 2010).

BDA adoption in this study is conceptualized as a second-order construct encompassing four dimensions of business value: strategic value, transactional value, transformational value, and informational value. These dimensions were adapted from the framework proposed by Raguseo and Vitari (2018). Strategic value denotes the perceived benefits of BDA at a strategic organizational level, while transactional value relates to operational benefits provided by BDA. Transformational value captures the perceived structural changes and future benefits facilitated by BDA, whereas informational value reflects the improvements in information quality derived from BDA solutions.

The TOE framework underpinning this study includes three primary constructs: technological factors, organizational factors, and environmental factors. Technological factors comprise six constructs - relative advantage, compatibility, complexity, uncertainty and insecurity, trialability, and observability - adapted from various studies (Chen et al., 2015; Ghobakhloo, Arias-Aranda et al., 2011; Thong, 1999; Lai et al., 2018). Organizational factors such as top management support and organizational readiness were also integrated into the study, drawing from existing literature (Chen et al., 2015; Priyadarshinee et al., 2017). The environmental factors considered in this framework - competitive pressure, external support, and government regulation - were adapted from relevant studies (Lai et al., 2018; Ghobakhloo, Arias-Aranda et al., 2011; Gupta and George, 2016).

Furthermore, the study assesses dimensions of firm performance to gauge respondents' perceptions of the impact of BDA adoption on improvements in financial and market performance. These measures were adapted from Raguseo and Vitari (2018) and Ji-fan Ren et al. (2017).

Table 1: Variable's Measurement Sources

Variables	Sources
BDA Adoption	Raguseo and Vitari, 2018
Relative Advantage	Chen et al., 2015; Ghobakhloo et al., 2011a; Premkumar and Roberts, 1999
Compatibility	Chen et al., 2015; Ghobakhloo et al., 2011a; Thong, 1999; Tornatzky and Klein, 1982
Complexity	Lai et al., 2018; Xu et al., 2017
Trialability	Etsebeth, 2013; Limthongchai and Speece, 2003; Moore and Benbasat, 1991
Uncertainty and Insecurity	Salleh and Janczewski, 2016; Shin and Shin, 2011
Observability	Limthongchai and Speece, 2003; Moore and Benbasat, 1991
Top Management Support	Chen et al., 2015; Lai et al., 2018; Priyadarshinee et al., 2017
Organizational Readiness	Chen et al., 2015
Competitive Pressure	Lai et al., 2018
External Support	Ghobakhloo et al., 2011a; Ghobakhloo et al., 2011b; Li, 2008
Government Regulation	Agrawal, 2015; Gupta and Barua, 2016; Lai et al., 2018; Li, 2008
Performance	Ji-fan Ren et al., 2017; Raguseo and Vitari, 2018

Source: Compiled by authors

4.2. Data Collection

This study focuses on Vietnamese SMEs within the manufacturing sector that have implemented BDA. The population consists of 300000 SMEs reported by the General Statistics Office of Vietnam (2020). We target owners and managers as representatives since they are typically the primary decision-makers regarding IT, BDA, and innovation adoption, possessing adequate knowledge to respond to the questionnaire. Potential participants were contacted to explain the study's objectives and clarify the concept of BDA. Contact information of willing firms' respondents was collected, and an online survey link, accompanied by a cover letter detailing the research aims and BDA definition, was distributed via email. To ensure relevance, a filter question was included asking respondents whether their firm utilizes big data analytics, ensuring that only SMEs with BDA experience were included.

From an initial pool of 500 potential respondents, 404 responses were received after follow-up calls at two-week intervals. Of these, 16 responses were incomplete or did not meet the inclusion criteria, resulting in 388 usable questionnaires and a response rate of 77.6%. Non-response bias was assessed through a t-test comparing early and late responses, which indicated no statistically significant differences at the 5% significance level, suggesting non-response bias was negligible (King & He, 2005). Additionally, Common Method Bias (CMB) was evaluated to ensure the validity and reliability of the study's constructs. Harman's single factor test indicated that CMB was not a major concern as no single factor dominated the variance (Podsakoff et al., 2003). Further, correlations between a marker variable and the main constructs showed no significant relationships, corroborating that CMB did not affect the study's outcomes (Lindell & Whitney, 2001). Thus, the study proceeds with confidence in its methodological robustness and validity of findings.

5. Results and Discussion

Initially, we assess the convergence of the constructs in this paper, including factor loadings, composite reliability (CR), and average variance extracted (AVE). BDA adoption was conceptualized as a second-order construct using a repeated indicator approach,

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adhering to the guidelines proposed by Hair et al. (2019). Specifically, factor loadings all above 0.7, CR values exceeding 0.5, and AVE values greater than 0.7 were considered indicative of satisfactory convergent validity. All constructs met or exceeded these thresholds, affirming their acceptable convergent validity. Discriminant validity was assessed using both the Heterotrait–Monotrait (HTMT) criteria criteria (Henseler et al., 2015) and the Fornell–Larcker criterion (Fornell & Larcker, 1981). HTMT values below 0.85 indicated that the constructs exhibited sufficient discriminant validity, in accordance with the standards outlined by Kline (2015). Additionally, the inter-construct correlations were lower than the square roots of their respective AVEs, further confirming good discriminant validity as suggested by Fornell and Larcker (1981). Thus, the authors proceeded to structural model path analysis, and we report the results in Table 2 below.

Table 2: Structural Model Path Analysis Results

Hypothesis	Relationship	Path Coefficient	Std. Dev.	Significance
H1	RA → BDA	0.094**	0.047	✓
H2	CMP → BDA	0.103***	0.041	✓
H3	CPX → BDA	-0.227***	0.055	✓
H4	UI → BDA	-0.249***	0.047	✓
H5	TR → BDA	0.086	0.038	X
H6	OB → BDA	0.146	0.052	X
H7	TMS → BDA	0.212*	0.049	✓
H8	OR → BDA	0.185**	0.052	✓
H9	CP → BDA	0.011	0.039	X
H10	ES → BDA	0.073*	0.040	✓
H11	GR → BDA	0.088	0.036	X
H12	BDA → FP	0.892***	0.031	✓
H13	BDA → MP	1.215***	0.035	✓

* Sig. 0.1; ** Sig. 0.05; *** Sig. 0.01

RA: Relative Advantage; CMP: Compatibility; CPX: Complexity; UI: Uncertainty and Insecurity; TR: Trialability; OB: Observability; TMS: Top Management Support; OR: Organizational Readiness; CP: Competitive Pressure; ES: External Support; GR: Government Regulation; BDA: Big Data Analytics Adaption; FP: Financial Performance; MP: Market Performance

Source: Authors' Computation

Among the six technological factors examined, it is contradicted to existing literature that trialability and observability have no significant impact on BDA adoption within SMEs. While being two critical factors influencing technology adoption, they may encounter specific challenges in the context of SMEs in Vietnam, thereby potentially hindering the adoption of BDA. Trialability refers to the ability of organizations to experiment with a technology before full-scale adoption, allowing them to assess its benefits and feasibility (Laurell et al., 2019). In Vietnam, SMEs often face financial constraints and limited access to technological resources. The cost associated with setting up BDA infrastructure and conducting trial runs can be prohibitive for many SMEs, restricting their ability to experiment with the technology before committing substantial resources. Moreover, the lack of readily available expertise and technical support further complicates the trialability process, as SMEs may struggle to effectively implement and evaluate BDA solutions without adequate guidance.

Observability, on the other hand, pertains to the visibility of technology benefits to others within the organization, which can influence decision-makers to adopt the innovation (Rogers, 2003). In the Vietnamese SME context, the tangible benefits of BDA may not be immediately visible or easily quantifiable, especially in industries where data-driven decision-making is not yet pervasive. Unlike larger enterprises that have the resources to implement and showcase the benefits of BDA on a broader scale, SMEs in Vietnam may lack the capacity to demonstrate the clear advantages of BDA adoption to their stakeholders. This limited observability may lead to skepticism among SME owners and managers about the real-world benefits and return on investment associated with adopting BDA, thereby slowing down the adoption process. Thus, while trialability and observability are crucial determinants of technology adoption, their effectiveness in facilitating BDA adoption among SMEs in Vietnam is tempered by financial constraints, limited technical expertise, and the challenge of demonstrating tangible benefits. Overcoming these barriers requires tailored strategies that address SMEs' specific needs and capabilities, possibly through government support, industry collaboration, and initiatives aimed at enhancing technical skills and awareness among SMEs in Vietnam.

In line with previous research by Gangwar (2018) and Lai et al. (2018), complexity was identified as a significant deterrent to BDA adoption among SMEs. This finding aligns with broader literature indicating that the complexity of adopting new technologies is exacerbated in SMEs due to limited internal expertise and resources (Ismail & Ali, 2013; Asiaei, 2019). For SME managers, the perceived difficulty and uncertainty surrounding BDA adoption often stems from concerns about their firm's readiness and capability to effectively utilize such advanced technologies. Considering these challenges, outsourcing BDA initiatives may emerge as a viable strategy for SMEs seeking to overcome internal limitations and leverage external expertise to facilitate successful adoption. The detrimental impact of uncertainty and insecurity on the adoption of BDA is well-documented in prior research. Business owners often cite privacy and security concerns as primary barriers to embracing data-related technologies (Priyadarshinee et al., 2017). Despite the prevalence of BDA outsourcing among SMEs, apprehensions about losing control over confidential data and the risk of information leaks to competitors can significantly hinder adoption. Therefore, establishing trust between BDA service providers and SMEs becomes crucial. Trust can be cultivated through the reputation of service providers or previous positive experiences with them (Choudhury & Sabherwal, 2003). Strategies such as early demonstration of security measures and leveraging referrals from satisfied clients are effective in building this trust. Additionally, investments in social media marketing can enhance service providers' reputations, thereby fostering trust among potential SME adopters (Kim & Ko, 2010).

In the context of SMEs in Vietnam, the adoption of BDA hinges significantly on perceived relative advantages over existing technologies. Relative advantage, a key determinant in technology

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adoption, refers to the perceived enhancement that a new technology offers compared to current systems (Baker, 2012; Kapoor, Dwivedi, & Williams, 2015). For SMEs, the decision to adopt BDA is heavily influenced by the perceived benefits it can bring to their operational efficiency and competitive positioning (Gu, Cao, & Duan, 2012). Studies by Ghobakhloo, Arias-Aranda et al. (2011) and Ullah and Qureshi (2019) suggest that SMEs are more likely to adopt new technologies like BDA if they believe the advantages outweigh those of their existing technological infrastructure. To facilitate BDA adoption among SMEs in Vietnam, it is essential to emphasize the tangible benefits that BDA can offer. Highlighting case studies or success stories from similar SMEs in Vietnam or other comparable markets could help illustrate the potential gains in operational efficiency, decision-making capabilities, and market competitiveness. Furthermore, providing demonstrations or trials of BDA solutions could allow SMEs to experience firsthand the advantages over their current systems, thereby reducing uncertainty and encouraging adoption. Compatibility, another critical factor, assesses the alignment of BDA with existing organizational practices and systems. Compatibility reflects how well BDA can integrate into the current workflows and culture of SMEs (Chen et al., 2015; Kapoor, Dwivedi, & Williams, 2014). Ensuring compatibility involves adapting organizational policies, processes, and training programs to facilitate smooth integration and utilization of BDA (Verma & Bhattacharyya, 2017; Gangwar, 2018). To enhance compatibility, BDA providers and consultants in Vietnam should offer customization options and flexible implementation strategies that cater to the specific needs and operational contexts of SMEs. Moreover, fostering a supportive ecosystem where SMEs can exchange knowledge and best practices related to BDA adoption can enhance compatibility. Establishing forums, workshops, or online platforms where SME owners and managers can share their experiences and challenges in adopting BDA could provide valuable insights and encourage peer learning. Government initiatives and industry associations in Vietnam could also play a pivotal role in promoting BDA adoption by offering incentives, subsidies, or technical assistance programs tailored to SMEs.

Furthermore, organizational factors such as top management support and organizational readiness have been identified as pivotal in facilitating BDA adoption among SMEs. Top management support is particularly crucial as owners/managers are key decision-makers whose vision and commitment determine the organizational climate for adopting new technologies (Asiaei, 2019; Maduku et al., 2016). Studies across various technological domains consistently highlight the role of top management in fostering an environment conducive to technological innovation and adoption (Alshamaila et al., 2013; Cruz-Jesus et al., 2019). Their support not only signals organizational priorities but also facilitates learning and diffusion of BDA capabilities throughout the firm (Asiaei, 2019). Hence, the active involvement and endorsement of top management are essential at all stages of BDA adoption within SMEs.

The significant association between organizational readiness and the adoption of BDA aligns with prior research on technology adoption within SMEs (Gangwar, 2018; Kandil et al., 2018; Kuan & Chau, 2001; Lai et al., 2018; Ramdani et al., 2013; Wen & Chen, 2010). For SMEs, embracing BDA is not straightforward without adequate technological infrastructure, financial resources, and skilled human capital. The absence of these prerequisites often hampers the adoption of BDA, as firms are unlikely to invest in technology without the necessary resources and capabilities. Therefore, financial investments and initial technological support are essential for outsourcing BDA solutions, while skilled personnel play a crucial role in effectively implementing these technologies.

Among the three environmental factors - competitive pressure, external support, and government regulation - external support emerges as a pivotal driver of BDA adoption among SMEs. The negligible impact of competitive pressure diverges from findings by Dal-woo, Dong-woo, and SoungHie (2015) and Ghobakhloo, Sabouri et al. (2011). In the Vietnamese context, the lack of significant multinational competition and low local adoption rates of BDA contribute to the minimal influence of competitive pressures on SMEs. Sanctions have limited substantial investments by multinational firms in Vietnam, thereby reducing competitive pressure on local SMEs. Moreover, the slow uptake of BDA among local competitors further diminishes competitive pressures within the market, making it a negligible factor in SMEs' decisions to adopt BDA.

Conversely, the significant correlation between external support and BDA adoption among SMEs is consistent with prior studies (Ghobakhloo, Arias-Aranda et al., 2011; Gangwar, 2018). According to Ghobakhloo, Arias-Aranda et al. (2011), SME CEOs are more inclined to adopt Information Systems (IS) when they perceive that service providers can fulfill their technological needs. Therefore, training and technical support offered by BDA service providers can alleviate concerns among SME managers regarding the technical skills required for implementing BDA solutions. Consequently, external support assumes a critical role in the decision-making process of SMEs grappling with human resource deficiencies in the realm of BDA implementation.

The findings of this study suggest that government regulations do not significantly influence the adoption of Big Data Analytics (BDA) among SMEs, a conclusion that contrasts with earlier research by Lai et al. (2018) and Ghobakhloo, Sabouri et al. (2011). One potential explanation for this negligible relationship is the perception among SMEs that the adoption of BDA represents a substantial investment, and that governmental incentives alone may not suffice to justify such expenditures. Moreover, the rapid changes in governmental regulations in contexts like Vietnam diminish the extent to which managerial decisions are guided by regulatory frameworks, particularly in the case of complex technologies such as BDA. Consequently, government regulations exert a limited influence on SMEs' decisions to invest in BDA within such environments.

Furthermore, the study underscores that BDA adoption significantly enhances both the marketing and financial performances of SMEs. Prior literature consistently highlights the creation of business value and enhanced organizational capabilities through BDA adoption (Mikalef, Boura et al., 2019; Müller et al., 2018; Raguseo & Vitari, 2018). Müller et al. (2018) affirm that BDA positively impacts marketing performance by enabling firms to develop products and services that deliver superior value to customers, thereby differentiating them from competitors. Similarly, studies by Ji-fan Ren et al. (2017) and Raguseo and Vitari (2018) emphasize that BDA enhances firms' profitability and customer retention capabilities. By leveraging data-driven insights, BDA enables SMEs to effectively monitor their operating environment, thereby facilitating informed decision-making processes (Popovič et al., 2018). Additionally, Lee et al. (2013)

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highlight that BDA adoption in manufacturing firms reduces waste, production costs, and the incidence of faulty products, thereby enhancing overall operational efficiency and performance. In conclusion, while government regulations may have limited influence on BDA adoption among SMEs, the strategic implementation of BDA significantly enhances both marketing effectiveness and financial performance. These findings underscore the transformative potential of BDA in empowering SMEs to optimize operations, innovate products and services, and gain competitive advantage in dynamic business environments.

6. Conclusion

Our research contributes theoretically by addressing gaps in understanding the drivers and outcomes of BDA adoption specifically among SMEs. While numerous studies have explored BDA adoption in large firms (Wang & Hajli, 2017; Wang et al., 2018), empirical research on SMEs in this context remains limited (Maroufkhani et al., 2019). SMEs differ significantly from large enterprises in terms of resource availability and organizational structure, making it essential to identify the most relevant TOE factors influencing BDA adoption in SMEs, particularly in regions like Vietnam. This study presents a consolidated model to evaluate how TOE factors impact BDA adoption and examines the subsequent effects of BDA adoption on SME performance. Results underscore the significance of factors such as complexity, perceived relative advantage, uncertainty and insecurity, compatibility, top management support, organizational readiness, and external support in shaping SME managers' decisions to adopt BDA. In contrast, factors like trialability, observability, competitive pressure, and government regulation showed no significant effects, highlighting distinct drivers of BDA adoption in Vietnamese SMEs compared to large firms, as well as SMEs from other countries.

Practically, the findings offer critical insights for SME managers and BDA service providers. They confirm that BDA adoption positively influences both market and financial performance in SMEs, addressing a notable gap in literature focused predominantly on large firms. Despite SMEs' historical hesitation due to uncertainties regarding BDA's benefits and adoption factors, this study affirms that strategic investments in BDA can enhance SME performance. The findings also emphasize the organizational and environmental considerations influencing BDA adoption decisions in Vietnam, highlighting the pivotal roles of top management support and external assistance. Effective managerial support entails providing financial backing, technical resources, skill development opportunities, and identifying competent BDA service providers. Moreover, complexities, uncertainties, and the need for external support underscore the importance of service providers' reputations, particularly in security measures, trial offerings, and comprehensive technical support, to facilitate BDA adoption among SMEs. Addressing SME concerns about technical complexity and security through accessible trials and support mechanisms is crucial for service providers aiming to promote BDA adoption effectively.

Several limitations affect the generalization of findings in this study. The sample was restricted to SMEs, characterized by different resource capabilities and organizational flexibility compared to larger enterprises. Future research should extend this model to include large firms for comparative analysis. Additionally, the study's focus on Vietnam, a nation under several constraints, which impacts competitive dynamics and government support for BDA adoption. Further research is needed to validate these findings in both developing and developed economies. Methodologically, the study's cross-sectional design and questionnaire-based approach limited the ability to establish causality among variables, necessitating future longitudinal studies to capture the dynamic nature of BDA adoption over time. Finally, future research could expand the conceptual framework by considering additional factors such as organizational culture, market pressures, and technical infrastructure, which may further enrich understanding of BDA adoption among SMEs.

In conclusion, BDA has emerged as a critical tool enhancing organizational efficiency and decision-making capabilities, yet its adoption among SMEs remains comparatively low (Coleman et al., 2016). Addressing this gap, this study leveraged the RBV and TOE framework to investigate the technological, organizational, and environmental drivers of BDA adoption and its impact on SMEs' financial and market performance. Findings underscored the nuanced effects of different technological factors on BDA adoption among SMEs, with complexity and uncertainties presenting challenges while trialability and observability proving beneficial. Organizational factors such as top management support and internal resources significantly influenced BDA adoption, whereas external support emerged as a critical environmental factor. The study's results emphasize that BDA adoption positively impacts both financial and market performance in SMEs, suggesting that strategic investments aligned with influential TOE factors could enhance SMEs' overall performance.

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