Application of the Technology- Organization- Environment Framework on Big Data Analytics Deployment in Manufacturing and Service

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ABSTRACT

The rising demand for Big Data Analytics (BDA) is essential for maintaining market competitiveness, providing valuable insights and opportunities for smarter business decisions and efficient operations. While big data offers several benefits, organisations in Malaysia are still in the infancy stage of adopting the technology. This study aimed to examine the determinant factors of Technology-Organization-Environment (TOE) in relation to the Big Data Analytics deployment by Malaysian organizations. Based on the TOE Framework, a survey questionnaire was distributed via email and google form to the existing companies in the manufacturing and service industries in Klang Valley. A total 116 responses were received. The study revealed that the deployment of BDA in Malaysia's manufacturing and service sectors was influenced by seven determinant factors (relative benefit, compatibility, organisational resources, top management support, competition intensity, regulatory support, and external support), while technological complexity and organisation size were not significant. Findings from the study provide a comprehensive analysis of factors influencing BDA technology adoption, utilizing the TOE as the comprehensive model to assist practitioners in making informed decisions. The study extended the utilisation of the TOE framework from the wider dimension that emphasised the technological aspect such as technology readiness, the usefulness of the technology, the complexity and technology compatibility within the organisation. From the practical perspective, this study provides an avenue for practitioners to learn the fundamentals of BDA adoption in various industries resulted in time and cost saving prior to effective decision making. The findings also highlight the government's crucial role in facilitating businesses' implementation of BDA, offering suggestions on incentives, precise standards, and lenient rules.

Keywords: Big Data, Data Analytics, Technology-Organization-Environment (TOE) Framework, Manufacturing and Service Industry, Malaysia.

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INTRODUCTION

Big data analytics is crucial in manufacturing and industrial services to gain competitive advantages. Digital transformation has altered data production, communication, and analysis, and organizations' responses to environmental change. Social media platforms contribute to the erosion of unstructured data creation in short timescales (Ghani, Hamid, Hashem, & Ahmed, 2019; Ishikiriyama & Gomes, 2019). Astounding amounts of diverse data are produced not only internally but also from public, private, and commercial sources. This phenomenon is known as big data (BD) and comprises both structured and unstructured data, such as written documents, web content, videos, audio, photographs, and sensor data, in addition to structured data like transactional records held in conventional databases and data warehouses. The massive amount of big data generated through the integration of users' background details and everyday activities in social media has gained popularity and is widely researched.

Big data is defined as collection of huge data sets comes from various of sources with a diversity of types and become difficult to process using the traditional data processing (Raut, Mangla, Gardas, Priyadarshinee & Narkhede, 2019; Piccarozzi & Aquilani, 2022). Some studies have demonstrated the power and impact of big data in current life and its importance as natural resources (Glaeser, Kominers, Luca, & Naik, 2018; Himuer et.al, 2023). For instance, the study by Himuer et. al. (2023) offers a comprehensive systematic survey by integrating artificial intelligence and big data analytics for building automation and management systems (BAMSs). Some authors proposed big data as massive volumes of unstructured and raw data from various sources, which come with high veracity and are in high volume and require high computing power to collect and process (Urus et al., 2023; Sivarajah et al., 2017). Big data is meaningless in a vacuum. Its promising value is unlocked only when it is leveraged to drive decision-making. Every organisation needs an efficient process to change high volumes of fast-moving and divergent data into substantial insights to enable such evidence-based and useful decision-making (Gökalp et al., 2022; Naeem et al., 2022). Sivarajah et al. (2017) argued that big data on its own has not offered valuable insights in its crude form; hence, the data needs to be analysed in order to provide its meaning, which led to big data analytics (BDA). BDA is regarded as a sub-process that consists of a combination of multiple information technology-enabled resources with the purpose of discovering knowledge, extracting insights, predicting outcomes, and consequently, creating competitive advantage and empowering businesses to support their strategic decision-making (Gökalp et al., 2022; Ishikiriyama & Gomes, 2019).

BDA is a powerful tool that allows organisations to extract valuable insights and information from large and complex data sets. It involves the use of advanced tools and technologies, as well as specialised skills and expertise, to process and analyse data from a variety of sources and types (Urus et al., 2023). Advances in BDA make it easier for organizations to work with enormous amounts of data, enabling them to better utilize the data and therefore better understand their customers

(Youssef et al., 2022). BDA, as a technology, has also brought about dynamic changes in the competitive corporate environment by supporting educated decision-making, innovation upgrades, higher productivity, and information interchange (Lutfi et al., 2022). Many major organisations have adopted BDA because of its advantages for a range of uses, including forecasting future market trends and analysing consumer behaviour and experiences to find fresh chances for development. Furthermore, to transform big data into useful values, organisations need organisational resources like a data-driven culture and organisational learning. Overall, BDA adoption benefits businesses by improving organisational performance (Dubey et al., 2020; Sivarajah et al., 2024; Raguseo & Vitari, 2018).

Based on the Big Data Market Research Report published in 2024, the big data market is experiencing unprecedented growth, with estimates indicating a substantial expansion in market size from USD 220.2 billion in 2023 to USD 401.2 billion by 2028. Market and Market Research, 2024, expects this significant growth to occur at a CAGR of 12.7% over the forecast period (2023–2028). As per the 2024 predictions, the world is expected to generate 181 zettabytes of data by 2025, and 2.5 quintillion bytes of data are created daily by internet users globally (Acumen, 2022). North America is leading the market and is expected to lead throughout the forecasted timeframe from 2022 to 2030, with the big data market share generated over US$ 57.2 billion in revenue in 2021.

The Asia-Pacific region is also expected to demonstrate the substantial growth rate of the big data market, which will record a CAGR of around 14% from 2022 to 2030 (Acumen, 2022). The APAC's big data market is expanding as a result of the expanding use of big data technologies like Apache and Hadoop, IoT devices, the expansion of the insurance and banking industries, and the penetration of novel technologies like connected devices. In Malaysia, BDAs have been recognised by the Twelfth Malaysia Plan, which covers the period from 2021 to 2025, as a significant change agent that will propel Malaysia to the forefront of sustainability and innovation. Malaysian firms are actively progressing from the ad-hoc stage to the maturity stage and subsequently the opportunistic stage (Wahab et al., 2021). In keeping with Malaysia's goal of becoming a developed country by 2025, the government has designated important digital domains to propel the ICT industry (Urus et al., 2023).

Therefore, the Malaysian government has made a significant effort to promote the use of BDA, which is expected to grow the big data analytics (BDA) market to US$1.9 billion (RM9.03 billion) in 2025 from US$1.1 billion (RM5.23 billion) in 2021, according to IDC studies of Malaysia Digital Economy Corporation (MDEC). Undoubtedly, the establishment of the comprehensive, state-owned Malaysian MDEC, is to be in charge of spearheading the development of the country's digital economy that supports talent development within the BDA realm in Malaysia. It is believed that it will facilitate Malaysia's talent and economic players to tap into the US$13 trillion in revenue projected to be added by data-fuelled applications in the global economy by 2030 (The Edge Malaysia, 2024). MDEC has also urged that the

BDA is central to Malaysia's digital economy, resulting in growth of other digital technologies, such as artificial intelligence (AI), the Internet of things (IoT), advanced automation and others.

Despite the tremendous growth of BDA, organisations in Malaysia are still lacking adequate ICT resources, mainly skilled manpower and state-of-the-art facilities. As a result, appropriately qualified personnel and a specialised technical infrastructure are required for broader BDA adoption. Hence, adequately trained manpower and dedicated technical infrastructure must be in place for greater BDA adoption among logistics firms (Wahab et al., 2021). The existing big data research focuses on technology, organisation, and the environment, and it has a favourable impact on corporate success. However, no theoretical framework has been developed that fully accounts for all of these opportunities for applying big data analytics, and it is entirely unknown how to anticipate the value of factors influencing the adoption of big data (Hong & Ping, 2020). Besides, past research on the BDA has not comprehensively considered determinants that influence BDA adoption (Sun, 2016; Agarwal, 2014; Wahab et al., 2021).

To address this knowledge gap, this study aimed to examine the determinant factors of big data analytics deployment based on the Technology-Organization-Environment (TOE) model in Malaysian manufacturing and service industries. The relationship between technological factors (relative benefits, compatibility, complexity), organisational factors (organisation resources, top management support, organisation size), and environmental factors (competition intensity, regulatory support, external support) was tested. The remainder of the paper is organised as follows: the next section presents the literature review and theoretical foundation. This is followed by the hypotheses' development and research framework. Subsequently, a description of the methodology is outlined. The results are presented in the following section. The final section presents the discussion and conclusion.

LITERATURE REVIEW

Conceptualization of Big Data and Big Data Analytics

Big Data and Big Data Analytics Concepts

Data characteristics have been the biggest challenge (Urus et al., 2023). Gupta and Rani (2019) stated that, currently, there is no standardised definition for big data. The constant evolution of big data development causes a debate on defining big data, as today's big data may be tomorrow's small data. Different researchers have distinct understandings of data characteristics (Sivarajah et al., 2017). The original and well-known definition is the 3Vs, which characterise big data as volume, variety, and velocity (Chen et al., 2012; Gantz & Reinsel, 2011; Kwon et al., 2014; Laney, 2001; Lin et al., 2020; Shah et al., 2014). Two more additional "Vs" –Veracity and Variability added to the characteristics (Gandomi & Haider, 2015; Mishra et al., 2021; Fosso Wamba et al., 2015). Sivarajah et al. (2017), in their study, added

visualisation, which is the seventh characteristic of big data. According to Hasan et al. (2022), the big data attributes fall under the “7 Vs” for big data, which include “Volume, Velocity, Variety, Variability, Veracity, Visualisation, and Value." Urus et al. (2023), they had synthesised the categorization of big data attributes ranging from 3V’s to 15V’s based on prior literature (Urus et al., 2023, pp. 77–80).

In this paper, big data encompasses "5Vs,” which were identified through data collection and analysis. These included Volume: a large amount of data, Variety: the different types of structures in the data flow, Velocity was defined as the frequency and speed of data generation. Veracity: trustworthy, authentic, and qualified data produced by the BD resources, Value: the potential benefits within the available data flow (Urus et al., 2023; Garmaki et al., 2023; Sivarajah et al., 2017). In order to uncover the potential value of large volumes of structured and unstructured data, BDA is a dynamic process and mechanism that analyses these raw data sets (Barbosa et al., 2018; Marr, 2022; Urus et al., 2023). The advent of data analytics simplifies the data management process. Analysing the data may facilitate the organisations’ ability to create new products, increase their efficacy and efficiency, and make smarter decisions by analysing the data (Urus et al., 2023). Data analytics also helps businesses to distinguish different characteristics of social, organisational, and technical threats that exist within big data (Al-Dmour et al., 2021), and BDA acts as a backbone that supports multiple aspects of business operations.

Applications of BDA

Over the years, researchers have developed a variety of BDA applications and tools. The application of BDA has been used across multiple industries, including healthcare, financial services, education, energy and gas, travel, crowdsourcing, and others (Hassan et al., 2021; Kaliraj & Devi, 2022; Urus et al., 2023). Chaudhary and Alam (2022) pointed out several applications of BDA in production and inventory management, marketing research, human resource management, as well as price setting and optimisation, among many others. Urus et al. (2023) had categorised the range of big data applications based on the various industries, as illustrated in the following diagram (Figure 1).

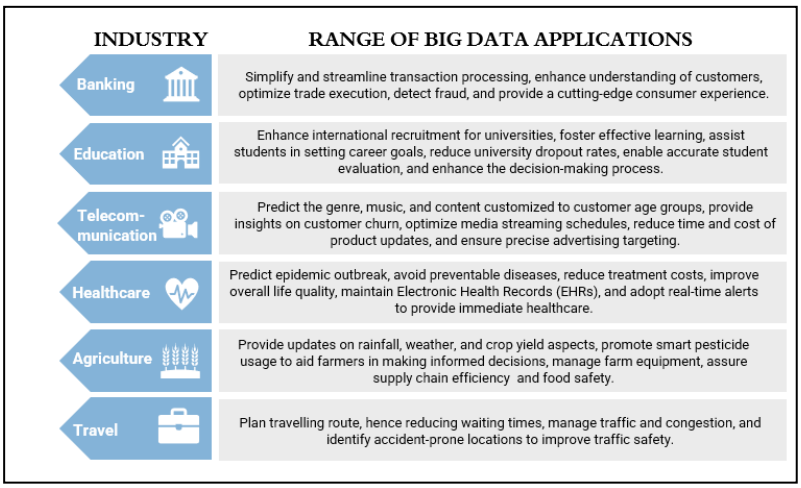

Figure 1: Big Data Applications by Industries
Source: Urus et al., 2023

BDA challenges

The future of BDA is constantly evolving over time. It is a dynamic cycle of technological innovation that pushes the limits of current device capabilities. New technologies will always face many challenges during the process of implementation and usage. Various industries have used BDA for various types of analytics. Its broad nature presents slightly different challenges that are unique to their own fields. The success of a big data project requires collaboration from multidisciplinary fields and from various sources. To derive the desired results, all parts of the organisational structure need to change simultaneously, such as tasks, technologies, people, and structure (Urus et al., 2023). Prior studies have suggested some challenges and barriers to BDA adoption (Hamzah et al., 2020; Ganesan et al., 2019; Silvarajah, 2017). Ganesan et al. (2019) stated that interdependent components such as people, processes, and technology play an important role in determining the success and failure of big data undertakings. Sivarajah (2017) had classified the BDA challenges into three major clusters: data challenges, process challenges, and management challenges. Urus et al. (2023) had further synthesised the challenges of BDA adoption under four main group categories: data analytic-related issues (such as data accessibility and sharing of information, data complexity, and data storage), security and privacy-related issues (cyberattack, privacy), process-related issues (selection and implementation of the appropriate tools and technologies), management-related issues (lack of resources, lack of internal support, lack of external support), and user-related issues (lack of knowledge and understanding of technology, lack of skills and expertise on BDA (Urus et al., 2023, pp. 91).

Theoretical Underpinning – The Technology-Organisation-Environment (TOE) Framework

The Technology-Organisation-Environment (TOE) model is widely used in technology adoption research (Jackson & Allen, 2024; Hossein et al., 2023; Wahab et al., 2021; Sun et al., 2018). TOE, which is based on technological, organisational, and environmental contexts, could provide some foundation for the analysis and consideration of suitable determinants for understanding innovation-adoption decisions. The TOE framework was initially developed by Tornatzky, Fleischer, and Chakrabarti (1990) in order to describe the influence of contextual factors in the adoption of an innovation. In this framework, there are three aspects of the organisation's context that will influence the adoption of the technology innovation: the technological context, the organisational context, and the external environmental context. These three contexts influence the way an organisation sees the need for, searches for, and adopts new technology.

This study aimed to examine the predictors of advanced technology for BDA deployment based on the TOE framework. The TOE framework proposes that a firm's decision on adopting and implementing technological innovations is influenced by the three relevant contexts of technology, organisational context, and environment (DePietro et al., 1990). Since this study investigated the factors that influenced BDA adoption surrounding the same components, it aligned with the idea behind the TOE model. Besides, these three contexts present both constraints and opportunities for technological innovation. The determinant factors included in this study were the relative advantages, compatibility, and complexity of technology. Organisational context comprised of organisational resources, top management support, and organisational size. While the context of the environment, included competition intensity, regulatory support, and external support, as these factors are considered the most influential factors that might affect the manufacturing and service industries in Malaysia.

The framework offered a holistic view of the multiple facets of an organisation rather than focusing on an individual's viewpoint, such as the technology acceptance model. The three independent variables selected (technological, organisational, and environmental) and the dependent variable, which is adoption of BDA, were supported by the theory. Therefore, from the perspective of new technological advancement adoption, the TOE framework was deemed suitable to be employed to investigate BDA adoption in the manufacturing and service sectors in Malaysia.

Hypotheses Development

Technology factors

BDA technology would improve the effectiveness of an organisation's operations, and it is progressively becoming a trending practice that many organisations are

adopting to extract valuable information from big data (Sivarajah et al., 2024; Luftiani et al., 2024; Wahab et al., 2021; Sivarajah et al., 2017). The deployment and use of BDA tools as an analytics process, with their strategic potential to drive new revenue streams and gain competitive advantages over business rivals, could improve operational efficiency (Sivarajah et al., 2024; Sivarajah et al., 2017). In this context, the current study examined the technological factors of complexity and compatibility, consistent with previous studies that considered these factors relevant in the adoption of innovation (Wessels & Jokonya, 2022; Aldossari et al., 2023).

The technological factor was the first independent variable, which consisted of three measurements: relative benefits, compatibility, and complexity. Several studies have used **relative benefits** to predict innovation adoption. Sun et al. (2018) listed relative advantage in the first rank, and ninety studies chose this factor in their investigation. Perceived usefulness or relative advantage was defined as the degree to which an individual believes that the use of an innovation helped to enhance her or his work. If business managers perceived that the use of a new technology was likely to enhance job performance and productivity, it would have a favourable influence on their attitude and intention to adopt a technology (Maroufkhani et al. 2020). Transformational benefits such as efficiency are most frequently recognised as the enhancement of productivity growth (Jensen et al., 2023; Urus et al., 2023; Wahab et al., 2021). To achieve transformational benefits, such as the reduction of operating costs, enhancement of returns on financial assets, and saving in supply chain management activities, were the other motivation factors behind the adoption of new technology (Jensen et al., 2023; Urus et al., 2023; Wahab et al., 2021). Jensen (2023) believed the transactional benefits were within the financial terms, inclusive of scalability, automatization, reduction of resource spends, reduction in response time, and improvement of the contribution margin by a percentage. banking sector. Urus et al. (2023) postulated that in the banking sector, BDA facilitates reducing customer problems, increasing bank revenue, and making bank services more transparent and comprehensible. Thus, the first hypothesis developed was:

Hypothesis 1 (H1): There is a significant relationship between the relative benefits and BDA deployment.

Compatibility has been a frequently cited as a driver of technology adoption (Bian et al., 2020). Compatibility examines "the degree to which a new system is consistent with the current system within the company" (Maroufkhani et al., 2020, p. 3). Compatibility also refers to the degree to which a new system is consistent with those that currently exist in the organisation (Awa et al., 2017). Firms can also increase their flexibility in terms of policies and procedures to promote high BDA adoption (Maroufkhani et al., 2020; Maroufkhani et al., 2023). BDA adoption requires that a system be well matched to current organisational IT resources and requirements (Yadegaridehkordi et al., 2020); innovations that match available technologies and current procedures are more readily accepted (Chatterjee and Kar, 2020; Shahzad et al., 2020). Based on these arguments, the second hypothesis proposed was:

Hypothesis 2 (H2): There is a significant relationship between compatibility and BDA deployment.

Complexity is defined as the degree of innovation perceived to be difficult to understand and use (Rogers, 2003). It is essential to understand the complexity associated with the new technology before making a decision to adopt it (Verma et al., 2018). As in technology adoption, compatibility is reflective of the technology's alignment with the organisation's business practices and culture (Baig et al., 2021). Thus, the complexity of innovation should be analysed to ensure the organisation is ready to face any challenges throughout the implementation process (Agrawal, 2015). The organisation believes that BDA adoption is a complex process and complex to use. Effectively planning big data processes on these platforms can be difficult. They involve complex ecosystems where developers need to discover the main causes of performance degradation in terms of time, cost, or energy. However, processing the collected logs and metrics can be a tedious and difficult task (Hernandez, Perez, Gupta, & Muntes-Mulero, 2018). Recent literature acknowledges the complex task of implementing BDA in organizations due to aspects such as data security and privacy, architecture availability, and technology diversity, which negatively influence its adoption (Maroufkhanie et al., 2020; Zamani, 2022). Hence, the third hypothesis was proposed:

Hypothesis 3 (H3): There is a significant relationship between complexity and BDA deployment.

Organisational factors

From the perspective of organisational factors, three measurements were discussed in this independent variable: organisational resources, top management support, and organisation size. **Organisational resources** were the first attribute included in the organisational factor, which referred to organisational resource availability. The intention of organisations to adopt new technology is influenced by the availability of technological resources. A study by Lai et al. (2018) found that IT infrastructure or capabilities did not have a direct effect on the intention to adopt BDA. They assumed the organisation could use strategic outsourcing to resolve technological or professional issues. They can still embrace big data with the help of external parties, such as software providers, even though organisations lack appropriate IT infrastructure. The debate on costs has also prompted researchers to concentrate their emphasis on resources, particularly financial resources, which have drawn the greatest attention. Lack of financial resources was studied to be one of the concepts negatively affecting the adoption of new technology among firms, particularly for those who have a lower tolerance for longer product development cycles (Zamani, 2022). Less attention was paid to the strategy, regulations, and infrastructure categories of concepts. Studies on strategy have primarily focused on the perceived risk of a specific technology (Shahzad et al., 2020), the inefficiency of strategic orientation in SMEs (Astuti et al., 2020), the lack of a clear strategy or communication (Al-Tit, 2020; Faridi and Malik, 2020), and the identification of these

factors as barriers to new technology adoption in SMEs. Therefore, we posited the fourth hypothesis.

Hypothesis 4 (H4): There is a significant relationship between organizational resources and BDA deployment.

Top management support has consistently been found to play a crucial role in the adoption of IT innovation (Gangwar et al., 2015; Amini & Jahanbakhsh Javid, 2023). For instance, Amini & Jahanbakhsh Javid (2023) urged that top management behaviour is considered an influential factor that can promote or inhibit the adoption of an innovation. Top management support refers to the degree to which top management understands the importance of the information technology function and the extent to which it is relevant to the activities (Park et al., 2015). Successful adoption of technology depends on management support (Khayer et al., 2020), while Maroufkhani et al. (2023) asserted that top management support mediated the relationship between complexity and BDA adoption. Therefore, management support is likely to promote BDA in the organisation. Top management support was looked at from various different perspectives of the initiative to integrate a new technology (Dey and Deb Nath, 2020), its influence on younger employees to innovate (Saka and Chan, 2020), examining a new technology (Asiaei and Rahim, 2019), and its role specifically in technology adoption in SMEs in developing countries (Anwer, 2019). Top managers play a critical role in creating a suitable environment for adopting BDA where sufficient resources are available for technology adoption (El-Haddadeh et al., 2021). The support of top managers is essential during the technology adoption process; thus, they would have a positive effect on BDA adoption (Youssef et al., 2022; Wang et al., 2009). Accordingly, the following was hypothesised:

Hypothesis 5 (H5): There is a significant relationship between top management support and BDA deployment.

Organisation size is believed to influence most organisational aspects, including resource availability, decision-making, and organisational structure (Hameed et al., 2012; Zamani, 2022). Smaller organisations faced challenges in finding resources, whereas bigger organisations generally have more resources to invent new innovations (Thong, 1999). While some researchers found a direct relationship between the size of the firm and technology adoption (Giotopoulos et al., 2017; Msomi et al., 2019), others discussed that the size of the firm plays a role according to the type of technology (Martñnez-Roman, 2020), and others did not find a correlation between the size of the firm and technology adoption (Vrchota et al., 2019). Thus, the sixth hypothesis proposed was as follows:

Hypothesis 6 (H6): There is a significant relationship between organization size and BDA deployment.

Environmental Factor

The third independent variable was an environmental factor, which was

measured by three subfactors: competition intensity, regulatory support, and external support. **Competition intensity** referred to the degree to which the organisation is affected by competitors in the market (Agrawal, 2015). Innovation adoption is demanding due to competitive pressure to maintain a competitive advantage in the industry. The organisation believes their competitor will gain advantages if they adopted BDA. Previous studies recognised competition intensity as an important prediction of technology adoption (Agrawal, 2015; Gangwar et al., 2015; Nguyen & Petersen, 2017; Park et al., 2015). It was contended that the increasing usage of BDA by competitors could motivate the owners and managers to successfully and professionally capture business intelligence and analytics to uphold the firm's competitive position in the marketplace (e.g., Lautenbach, Johnston, & Adeniran-Ogundipe, 2017; Zamani, 2022). Other studies, such as those by Lautenbach et al. (2017), found that increasing BD usage among competitors could work to pressure the owners and managers to capture business analytics and intelligence in order to obtain and maintain a competitive market status. The mixed results on competitive pressure were reported in prior studies such as the insignificant result for this factor affected on technology adoption reported by Wahab et al. (2021) and Lutfi et al. (2022) and contrasted with those reported by the prior study of Salwani et al. (2009), Hence, this study proposed the following hypothesis for testing:

Hypothesis 7 (H7): There is a significant relationship between competition intensity and BDA deployment.

Regulatory support, such as government support, is leveraging the diffusion and adoption of information technology (Lai et al., 2018). The regulatory environment is proven to be a critical factor affecting innovation adoption. Top management will consider adopting an innovation if there are standards or laws that support the adoption and adequate legal protection is available for post-BDA adoption. The use of BDA might also be driven by government influence. In related studies, Youssef et al. (2022) and Lutfi et al. (2023) revealed that firms with high regulations and pressure levels received from the government have a higher likelihood of adopting BDA. Firms' adoption of big data may increase if government rules and policies encourage them towards it and if technological standards and legislation are in favour of it (Lutfi et al., 2023; Lutfi et al., 2016). Organisations facing high levels of government pressure and regulations have the likelihood of adopting cloud technology based on prior studies (Lutfi et al., 2023; Wahab et al., 2021). Thus, the following hypothesis was proposed:

Hypothesis 8 (H8): There is a significant relationship between regulatory support and BDA deployment.

External support refers to the availability of support for implementing IT adoption by organisations such as third-party vendors, the community, and agencies (Maroufkhani et al., 2023; Maroufkhani et al., 2020; Biney, 2019; Gangwar, 2018). Other literature used trading partner readiness, which is external support, as a factor that influences the adoption of big data (Sun et al., 2018) and ranks as a second factor in environmental context. This study also followed prior literature (Maroufkhani et

al., 2023; Maroufkhani et al., 2020) that suggested that external support played a substantial role in adopting BDA among SMEs. Therefore, the ninth hypothesis was put forward:

Hypothesis 9 (H9): There is a significant relationship between external support and BDA deployment.

The following (Figure 2) depicts the research framework and hypotheses development used for this study.

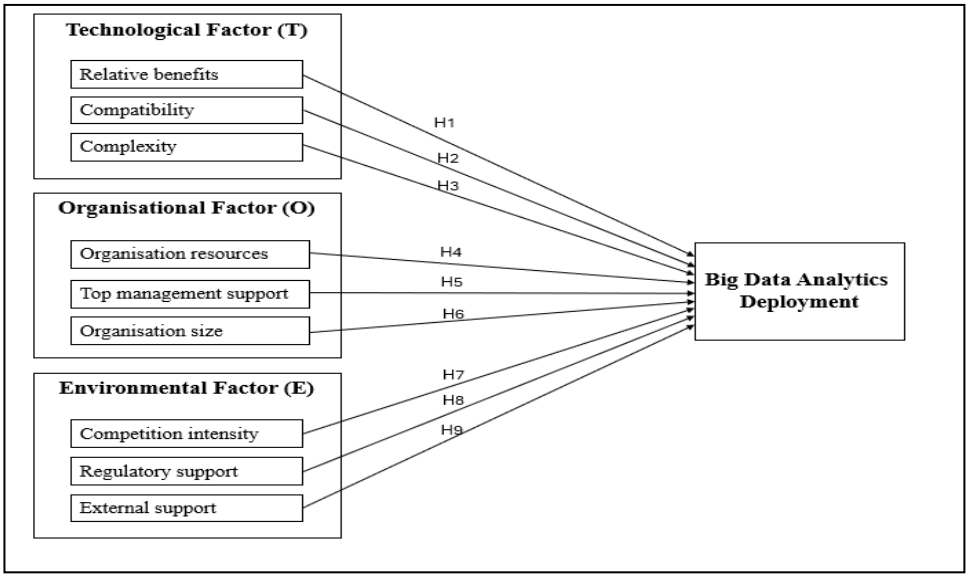

Figure 2: Research Framework
Source: Authors' Own Construct, 2024

Population and Sample of the Study

To achieve the goals and objectives of the study, a survey was done through the distribution of questionnaires answered by organisations that had utilised BDA. The unit of analysis was the existing organisations in the state of Selangor and Wilayah Persekutuan Kuala Lumpur. Thus, respondents were randomly selected from these organisations. The term organisation has been defined and interpreted differently by different authors (Rafaeli, 1996). It is a process that involves bringing individuals together to achieve specific objectives. In the current study, organisation referred to companies or business organisations. Companies was chosen because BDA technology was used by many branches of business (Agrawal, 2015). Selangor and Kuala Lumpur were chosen because these two states had the highest number of existing companies in Malaysia. A total of 1100 questionnaires were distributed; 60 questionnaires were sent by mail to the respective organisations. Another 150 questionnaires were randomly distributed to another fifteen organisations from the ROC listing using mail, and another 250 questionnaires were distributed by hand to

the human resources departments of the organisations. Another 640 questionnaires were distributed by email and Google Form. A total of 116 responses were received, resulting in a response rate of 30%.

Survey Instruments

The survey instrument included 42-item questionnaires. Based on three previous studies (Agrawal, 2015; Nguyen and Petersen, 2017; and Lai et al., 2018), the questionnaire was designed to capture the respondents' opinions about big data analytics. The questionnaire also aimed to pinpoint the factors that motivated an organization to embrace BDA. A five-point Likert scale ranging from 1 as 'Strongly Disagree' to 5 as 'Strongly Agree' was used in the questionnaire as a measurement scale for this study. The questionnaire used in the study consisted of three sections, which were Sections A, B, and C. The respondents had to answer all the questions in Sections A, B, and C. Section A consisted of six questions, which included age, working experience, position in the organisation, type of industry, the status of BDA adoption, and the software used. The current study applied descriptive analysis to study the respondent's profile. Mean, median, and percentage were used to analyse this section. The following **Table 1** outlines the measurements used for the demographic profile of respondents.

Table 1: Measurement for Demographic Profile

Question		Measurement
Q1	Age	Below 25 years old 26 to 35 years old 36 to 45 years old Above 46 years old
Q2	Years of Experience	Less than 5 years 6 to 10 years 11 to 20 years More than 20 years
Q3	Position in organization	Top Management Managerial Level Middle Level (Executive/ Senior Executive) Supervisory Level
Q4	Organizational Industry	Manufacturing Services Telecommunication Healthcare Construction Retails Information Technology Oil and Gas Banking/ Financial/Insurance
Q5	Adoption of BDA	Others Yes No

In Section B, respondents were asked about their understanding of factors that influenced the adoption decision by organisations in BDA. There were thirty (30) questions to address the independent variables in this study. Three independent variables, which were factors that influenced the adoption decision, were selected. Those factors were measured by a few questions in the subfactors. In Section C, respondents were asked about organisations adoption of BDA. There were six (6) questions to address the dependent variables in this study, which were adopted from Mansour & Ashour (2013). The adoption of BDA comprised technology, employees, and competitiveness aspects. The following **Table 2** outlines the measurements used for both independent and dependent variables.

Table 2: Summary of Dependent and Independent Variables

Variable	Measures	Description	References
Dependent			
The Adoption of BDA	- Attractive and economic option to organization - Increase employee technical knowledge - Employee's quick learner of new technology - Increase employees' skills - Maintain competitive advantage	Measurement for adoption of BDA	Mansour & Ashour, 2013
Dependent			
Technological	- Relative Benefit - Technology Compatibility - Technology Complexity	Use of big data analytics software	Agrawal (2015) Nguyen & Petersen (2017)
Organisational	- Organisation Resources - Top Management Support - Organisation Size	Financial and technical competency	Agrawal (2015) Nguyen & Petersen (2017)
Environmental	- Competition Intensity - Regulatory Support - External Support	External parties influence and support	

Measurement of Variables

Table 3 below depicts the measurement for dependent and independent variables.

Table 3: Measurement of Dependent and Independent Variables)

Variables	Item	Measurement
Adoption of BDA Technology (DV)		
BDA Technology	DV1	BDA technology is an attractive technological option to the organisation.
	DV2	BDA technology is an attractive economic option to the organisation.
	DV3	Our employees have equal or better technical knowledge than our competitors by using BDA technology.
	DV4	Our employees have an ability to quickly learn and apply new information technologies.
	DV5	Our employees have the skills and knowledge to manage IT projects in the current business environment.
	DV6	The organisation focuses on new technology which aim to maintain competitive advantage
Technological Factor (IV)		
Relative Benefits	RA1	BDA technology would improve the effectiveness of my organisation's operations.
	RA2	BDA technology would provide my organisation with valuable information for decision making.
	RA3	My organisation expects BDA technology to help in reducing costs.
	RA4	My organisation expects BDA technology to help in quick real-time data capturing and analysis.
Compatibility	CP1	Existing beliefs/values of my organisation are consistent with the changes introduced by BDA technology.
	CP2	BDA technology is compatible with existing infrastructure in my organisation
	CP3	The changes introduced by BDA are consistent with existing practices in my organisation
	CP4	The development of BDA technology is compatible with the existing experiences of my organisation on similar technology.
Complexity	CX1	My organisation believes that BDA technology is complex to use.
	CX2	My organisation believes that BDA adoption is a complex process.
Organisational Factor (IV		
Resources	OR1	IT infrastructures of my organisation is available to support BDA-related applications
	OR2	My organisation has the financial resources to adopt BDA technology.
	OR3	My organisation has no difficulties in providing all the necessary resources (e.g. funding, people, time) to adopt BDA technology.
	OR4	

Top Management Support	TM1	My organisation has a sound knowledge of BDA technology.
	TM2	Top management believe that the investment/potential investment and expenditure in BDA technology is worthwhile.
	TM3	Top management believes that this technology has potential strategic value.
		Top management support is important to provide the resources for my organisation to use BDA technology.
Organisational Size	OS1	Total capital of my organization is more compared to the industry.
	OS2	Returns of my organization are high compare to the industry.
	OS3	Employee strength at my organisation is more compared to the industry.
Environmental Factor (IV)		
Competition Intensity	CI1	My organisation experienced competition intensity to implement BDA technology.
	CI2	My organisation would have faced competitive disadvantage if BDA technology had not been adopted.
	CI3	My organisation believes it is a strategic necessity to use this technology to compete in the marketplace.
	CI4	My organisation believes that our competitors get many advantages if they adopt this technology in their organisation.
Regulatory Support	RS1	Adequate legal protection supports post-BDA technology adoption.
	RS2	The use of BDA technology is driven by the government influence
	RS3	Standards/laws support adoption of BDA technologies.
External Support	ES1	The key trading partners of my organisation encouraged BDA technology.
	ES2	There are agencies in the community who provide training on this technology.
	ES3	Technology agencies actively market this technology by providing incentives for adoption.

RESULTS AND DISCUSSION

Demographic Analysis

Table 4 depicts the age distribution of respondents, where 46.6% were between 36 to 45 years old, while only 8% were above 45 years old. These results suggested that most respondents belonged to a mature age group that was more familiar with

technology and used it extensively in their work. Conversely, the underrepresentation of the older group may reflect their limited exposure to and comprehension of emerging technologies. This finding is consistent with the research report from the Centre for Research and Education on Ageing and Technology Enhancement (CREATE), which found that older adults were less likely than younger adults to use technology in general, computers, and the World Wide Web (Czaja et al., 2006).

In terms of years of working experience, the majority, 45 respondents (38.8%), had between 11 to 20 years of working experience, while only 15 respondents (12.9%) had more than 20 years of working experience. The demographic for an individual's working position showed that the majority of respondents were in the middle level (executive or senior executive), comprising 60.3% of the total 116 respondents. Only 1.7% were at managerial levels. As displayed in Table 2 the industry sectors where manufacturing organisations had the highest representation (25.9%). This could be attributed to the increasing use of electronic devices, sensors, and digital machines, such as RFID technology, in shop floors, production lines, and factories. This has led to a massive amount of data in the industry, making big data analytics a valuable tool for improving operations. From the perspective of BDA adoption, 58.6% of the respondent's organisations (68 organisations) had not yet adopted BDA, while 41.4% (48 organisations) had. This indicated a lower level of adoption among Malaysian organisations.

Table 4: Demographic Profile

Variable	Details	Frequency	Percentage (%)
Age	Below 25 years old	14	12.10
	26 to 35 years old	38	32.80
	36 to 45 years old	54	46.60
	Above 46 years old	10	8.60
	Total	**116**	**100.00**
Years of Experience	Less than 5 years		
	6 to 10 years	30	25.90
	11 to 20 years	26	22.40
	More than 20 years	45	38.80
	Total	15	12.90
		116	**100.00**
Position in organisation	Top Management	2	1.70
	Managerial Level	30	25.90
	Middle Level (Executive/Senior Executive)	70	60.30
	Supervisory Level	14	12.10
	Total	**116**	**100.00**
Organisation's Industry	Manufacturing	30	25.90
	Services	21	18.10
	Telecommunication	13	11.20
	Healthcare	1	0.90
	Construction	8	6.90
	Retails	2	1.70
	InformationTechnology (IT)	19	16.40

	Oil and Gas	4	3.40
	Banking/Financial/Insurance	9	7.80
	Others	9	7.80
	Total	**116**	**100.00**
Adoption of BDA	Yes	48	41.40
	No	68	58.60
	Total	**116**	**100.00**

Table 5 shows the mean score and standard deviation for the three subfactors in technological factors: relative advantage, compatibility, and complexity. Respondents believed that BDA technology would improve the effectiveness of an organisation's operations and help in quick real-time data capture and analysis (M = 4.08, SD = .854), as three items in the relative benefits category surpassed a mean score of 4.00. Most respondents believed their existing beliefs, infrastructure, practices, and experiences were compatible with the new technology (M=3.68, SD =.798), while the highest rank in technology complexity was that the majority of respondents believed the BDA technology was complex to use (M = 2.40, SD =.709). Despite its complexity, the results indicated that technological factors like relative benefits and compatibility impacted the adoption of BDA.

Table 5 further displays the organisational factors in three measurements, which were organisational resources, top management support, and organisation size. The result showed that most respondents believed their organisations had IT infrastructure that was available to support BDA-related applications (M = 3.67, SD =.873). The result revealed that the majority of respondents agreed that top management support was important to provide the resources to use BDA technology (M = 3.90, SD =.838). The majority of the respondents also agreed in terms of organisation size that employees' strength in their organisation was greater compared to other organisations in the industry (M = 3.61, SD =.789), which was the most influential factor in adoption. Table 5 presents the rank of items in environmental factors, which were measured by competition intensity, regulatory support, and external support. The highest mean was 3.73, SD =.848, and respondents believed that their competitors will get many advantages if they adopted the technology. Meanwhile, adequate legal protection supports post-BDA technology adoption had the highest rank (M = 3.84, SD =.768), and the lowest mean score for the item of BDA use was driven by government influence (M = 3.61, SD =.842). Based on the view of external support, the highest mean score was 3.65, SD =.794, which was shared by items 1 and 3. Item 1 was key trading partners encouraging BDA technology, and Item 3 was technology agencies actively marketing the technology by providing incentives. Meanwhile, the lowest ranked was M = 3.59, SD =.834. It showed that respondents agreed that there were agencies in the community that provided training on this technology, like MDEC and ADAX.

Table 5: Descriptive Analysis

Variable	Mean	Std Dev	Cronbach Alpha
Deployment of BDA Technology	3.817	.761	.888
Technological Factor:			
Relative Benefits			.883
RA1	4.02	.823	
RA2	3.81	.854	
RA3	4.02	.844	
RA4	4.08	.854	
Compatibility			.892
CP1	3.68	.798	
CP2	3.65	.772	
CP3	3.66	.791	
CP4	3.63	.752	
Complexity			.905
CX1	2.40	.709	
CX2	2.37	.741	
Organisational Factor:			
Organisation Resources			.870
OR1	3.67	.873	
OR2	3.62	.851	
OR3	3.47	.918	
OR4	3.53	.937	
Top Management Support			.854
TM1	3.67	.873	
TM2	3.82	.809	
TM3	3.67	.838	
Organization Size			.847
OS1	3.47	.763	
OS2	3.54	.751	
OS3	3.61	.789	
Environmental Factor:			
Competition Intensity			.879
CI1	3.48	.763	
CI2	3.68	.881	
CI3	3.72	.919	
CI4	3.73	.848	
Regulatory Support			.856
RS1	3.84	.768	
RS2	3.61	.842	
RS3	3.66	.803	
External Support			.838
ES1	3.65	.794	
ES2	3.59	.834	
ES3	3.65	.794	

Instrument Validations

The validity test indicated that all items scored above the accepted value of 0.4, indicating that they were all important. Cronbach's alpha for the first subscale, which measured the adoption of BDA, was found to be.888, indicating good reliability. The other subscales for all three factors also showed good reliability, with values falling in the range of.9 > α ⩾.8. The overall Cronbach's alpha for all 36 items in the questionnaire was.965, indicating an excellent level of reliability. The data was normally distributed, as shown by skewness and kurtosis of -.199 and -.379, respectively. The correlations between the variables were acceptable and did not appear to suggest any multicollinearity problem. The highest correlation was recorded between organisational factors—top management support and BDA technology adoption with a coefficient of.738, $p < 0.01$. Moreover, tolerance for the measured items was more than 0.1 and the VIF value was less than 10, indicating no multicollinearity problems.

Regression Analysis

Hypothesis testing was carried out to test whether the posited relationship in H1 until H9 is true. **Table 6** presents the results of the multiple linear regression analysis, which measured the relationship between the multiple independent variables (technological factor, organisational factor, and environmental factor) and the dependent variable (BDA adoption). The study adopted the following multiple regression model.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Where:
Y = Big data analytics adoption
β_0 = Constant
X_1 = Technological factor
X_2 = Organisational factor
X_3 = Environmental factor
ε = Error term

The results of a multiple regression analysis indicated significant relationships between various factors and BDA technology adoption. Specifically, technological factors showed a positive and significant relationship with the adoption of BDA technology ($p < 0.05$). Similarly, a significant positive relationship was found between organisational factors and environmental factors ($p < 0.01$) and the adoption of BDA technology. These findings suggested that organisations may benefit from focusing on these factors when considering the implementation of BDA technology.

Table 6: Multiple Linear Regression Results

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig
	β	Std. error	Beta		
Constant	.369	.309		1.193	.235
Technological Factor:					
Relative Benefit	.239	.0.88	.278	2.721	.008
Compatibility	.405	.088	.448	4.589	.000
Complexity	-.026	.067	-.029	-.381	.704
Organizational Factor:					
Organisational Resources	.178	.068	.221	2.606	.010
Top Management Support	.465	.070	.562	6.680	.000
Organisational Size	.057	.077	.062	.739	.461
Environmental Factor:					
Competition Intensity	.283	.0.78	.339	3.612	.000
Regulatory Support	.183	.084	.213	2.169	.032
External Support	.231	.082	.265	2.822	.006

Based on the multiple regression analysis, seven of the nine hypotheses were supported, while two hypotheses were found insignificant. Overall, the following **Table 7** presents the summary of the hypotheses results.

Table 7: Summary of Hypotheses Results

No	IV	Hypotheses Statement	Findings
H1	Relative Benefit	Relative benefits significantly influence the deployment of BDA	There was ***a significant positive*** relationship between relative benefit and BDA deployment.
H2	Compatibility	Compatibility significantly influences the deployment of BDA	There was ***a significant positive*** relationship between technology compatibility and BDA deployment.
H3	Complexity	Complexity significantly influences the deployment of BDA	There was ***no significant* positive** relationship between technology complexity and BDA deployment.
H4	Organisational Resources	Organisational resources significantly influence the deployment of BDA	There was ***a significant positive*** relationship between organisational resources and BDA

			deployment.
H5	Top Management Support	Top management support significantly influences the deployment of BDA	There was ***a significant positive*** relationship between top management support and BDA deployment.
H6	Organisational Size	Organisational size significantly influences the deployment of BDA	There was ***no significant positive*** relationship between organizational size and BDA deployment.
H7	Competition Intensity	Competition intensity significantly influences the deployment of BDA	There was ***a significant positive*** relationship between competition intensity and BDA deployment.
H8	Regulatory Support	Regulatory support significantly influences the deployment of BDA	There was ***a significant positive*** relationship between regulatory support and BDA deployment.
H9	External Support	External support significantly influences the deployment of BDA	There was ***a significant positive*** relationship between external support and BDA deployment.

Discussion of Findings

The study revealed a significant positive relationship between relative benefit and BDA adoption, aligning with previous researches by conducted by Jensen et al., (2023), Wahab et al. (2021), Lai et al. (2018), Verma and Bhattacharyya (2017) and Verma (2017). They have suggested that decision-makers' perception of BDA technology's strategic value or relative advantage significantly influenced their adoption, highlighting its potential contribution to organizational value. The result that showed a significant positive relationship between technology compatibility and BDA adoption was consistent with the studies by Wahab et al. (2021), Baig et al. (2021), Verma and Bhattacharyya (2017), Agrawal (2015), and Wang, Wang, and Yang (2010). Compatibility was an important characteristic of BDA as a technological innovation. Organizations expect compatibility with their existing beliefs, infrastructure, and employees' knowledge and skills. Kamal (2006) suggested that BDA developers are increasingly interested in compatibility, focusing on the integration level of BDA technologies. Our finding also contradicted with Lutfi et al. (2022) that postulated that compatibility appeared to be of insignificant influence towards the BDA adoption. Nevertheless, there was no significant relationship between technology complexity and BDA adoption. This finding aligned with Waqar et al., (2023) where Technology complexity did not influence BDA adoption. This is because organisations gave more value to the benefits that new data analytics techniques bring in rather than the technology complexity. This finding contradicts the findings of Agrawal (2015) and Verma and Bhattacharyya (2017), where complexity was observed to have a significant negative influence on BDA adoption. However, the current finding was supported by the study of Lai et al. (2018), which

found that there was no significant relationship between technology complexity and the intention to adopt BDA technology.

In terms of organisational factors, the regression analysis revealed a significant positive relationship between organisational resources and the adoption of BDA technology. This finding was consistent with Verma and Bhattacharyya (2017) which suggested that the readiness of an organisation, in terms of technology, financial, and other related resources, was crucial for the successful adoption of new technologies such as BDA. The organisation's competency to provide all the necessary resources seemed to be a key factor influencing the decision to adopt BDA. Secondly, the study found a significant positive relationship between top management support and the adoption of BDA technology. This finding was not surprising, as top management support had been identified as an important factor in the adoption of new technologies in previous studies by Maroufkhani et al. (2023), Waqar et al. (2023), Verma and Bhattacharyya (2017), and Lai et al. (2018). Therefore, an organization can more easily navigate the complexity of adopting BDA technology with greater top management support. Top management support is crucial in promoting data-driven culture by allocating resources, investing in technologies, and encouraging employees to embrace data-driven practices across departments.

The study found no significant positive linear relationship between organisational size and the adoption of BDA technology. This finding contrasted with the finding by Agrawal (2015), which suggested that organisational size is a key variable influencing BDA adoption. Larger firms had a greater resources and knowledge to assimilate BDA and economies of scale to derive maximum benefit, so firm size has a positive effect on BDA adoption. However, in this study, the sample of respondents' organisational size did not indicate the intention of the organisation to adopt BDA, as the availability of outsource resources could accommodate the needs of those organisations in adopting BDA technology. The regression analysis results revealed a significant positive relationship between competition intensity and BDA technology adoption through the lens of environmental factors. This finding was consistent with the studies of Park et al. (2015) and Lai et al. (2018), who suggested that when competitors widely adopted BDA technology, firms were urged to adopt BDA, regardless of its complexity. Pressure from competitors, along with technological complexity, influenced the adoption decision-making process. In this regard, keeping up with competitors became more important than the complexity of the technology.

Furthermore, the study identified a significant positive relationship between regulatory support and the adoption of BDA technology, which was consistent with the findings of Wahab et al. (2021), Lai et al. (2018), and Kwon et al. (2014). Government support and policy act as crucial infrastructure for the diffusion of BDA in firms. Government roles, such as providing public data, fostering experts, protecting intellectual property, and regulating privacy and security, have a positive effect on the relationship between top management support and adoption intention. Top managers are often sensitive to governmental orientation, and they respond to

official policy and regulation. A supportive regulatory environment positively influenced the diffusion of innovations. External support is expected to influence the adoption and assimilation of BDA technology due to the number of vendors and third-party agencies offering BDA-related services. The study found a significant positive linear relationship between external support and the adoption of BDA technology. However, this finding contradicts the study of Nguyen and Petersen (2017), which found no support for a significant relationship between external support and the adoption of BDA technology. This inconsistency may be due to factors such as the availability of external support and the organisation's size, which may not require outside support to adopt BDA technology.

CONCLUSION AND IMPLICATION

Based on the results, out of nine hypotheses developed, seven were supported (H1, H2, H4, H5, H7, H8, and H9), while the other two, H3 and H6, were rejected. This indicated that relative benefit, compatibility, organisational resources, top management support, competition intensity, regulatory support, and external support influence the deployment of BDA in the manufacturing and service sectors in Malaysia. The findings of this study showed that technology complexity was not significant in influencing BDA deployment. Similarly, organisation size was also found not to have a significant influence on the adoption of BDA technology. From a theoretical perspective, this study provides a meaningful and wider view of investigating the influential factors in adopting BDA technology. Compared to other theories used to investigate technology acceptance, the TOE model was found to be the most comprehensive because it covered wider dimensions, which are technological, organisational, and environmental contexts. These contexts will look at the technology aspects, such as technology readiness, the usefulness of the technology, its complexity, and whether the new technology is compatible with the organisation’s existing technology. From a practical perspective, the findings have a number of important ramifications for the manufacturing and service sectors. This study showed a positive correlation between BDA adoption and organisational, technological, and environmental aspects. By attempting to comprehend the advantages of BDA adoption, organisations can develop a clearer attitude and a more insightful understanding of the findings this study could offer.

This research is significant as it provides better insight to practitioners, academicians, and researchers. Practitioners would be able to identify which factors need to be considered before making a decision to adopt the technology. Practitioners in the organisations could be the top management or accountants. Top management, who are responsible for business strategic decisions, will obtain a guide on which factors they need to consider before they decide to adopt this technology. Additionally, this study provides a platform for practitioners to learn the fundamentals of BDA adoption in various industries, thereby saving them money and time. The study's findings also affirm the government's role in facilitating businesses implementation of BDA. In order to communicate with the appropriate authorities,

businesses should cooperate with one another through trade groups. Through these encounters, businesses could provide suggestions to the government about the provision of alluring incentives, precise standards, and lenient rules. If these suggestions are effectively taken into account, the manufacturing and service sectors will benefit from improved legislative and administrative processes, which will speed up and broaden the implementation of BDAs.

Limitation of the Study

Throughout the interpretation of the hypothesised relationships, the study has several limitations. Firstly, the dispersal of the survey samples was concentrated in the Klang Valley (organisations in Selangor and Kuala Lumpur). Even though the samples covered most of the sectors, the organisation's demographic characteristics, such as location, could have influenced the result of the study, as the selected organisation is located at the hub of technology development in Malaysia. Hence, there could be more challenges, and the influential factors need to be considered for the organisation to adopt BDA in the other states. Besides, in terms of the respondent's industry background, the findings showed that the majority of the respondents were from the manufacturing sector, and currently most of the manufacturing companies have moved to IR 4.0. The findings might not represent the other industries. The current study employed a quantitative method, which limited the findings which could have been obtained via a qualitative study such as the observed influencing factors for BDA adoption. Hence, an in-depth understanding of the challenges that would hinder the successful adoption of BDA technology could not be presented in this study and opens up room for future research.

Future Research

Further research in this field of study is highly recommended. Since the world and Malaysia, in particular, are moving into the era of Industrial 4.0, of which BDA is one of the pillars, it will be a major and valuable contribution to academicians, practitioners, the government, and related agencies. The current study recommends that other researchers widen the sample and cover the other states to find out if the factors that influenced the organisations in Selangor and Kuala Lumpur to adopt BDA technology are relevant to the organisations in the other states. In-depth studies are also recommended for future research, where researchers could do qualitative studies instead of quantitative studies to have a better understanding of the subject matter. From the perspective of the theories adopted in the study, future researchers could apply other popular theories such as TAM and DOI to investigate this topic further.

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REFERENCES

Acumen (2022), Data Analytics Market Size - Global Industry, Share, Analysis, Trends and Forecast 2022 – 2030, Acumen Research and Consulting https://www.acumenresearchandconsulting.com/data-analytics-market

Aggrawal, N., Ahluwalia, A., Khurana, P. and Arora, A. (2017) 'Brand analysis framework for online marketing: ranking web pages and analyzing popularity of brands on social media', *Social Network Analysis and Mining*, Vol. 7, No. 1, p.21.

Ahmed, K.A. and Kranthi, A.K. (2019) 'Determinants of m-ticketing adoption using smartphone app among IT employees of Bengaluru city – an extended UTAUT2 approach', *International Journal of Business Innovation and Research*, Vol. 19, No. 1, pp.57–79.

Al-Dmour, A., Al-Dmour, R. H., Al-Dmour, H. H., & Ahmadamin, E. B. (2021). The effect of big data analytic capabilities upon bank performance via FinTech innovation: UAE evidence. *International Journal of Information Systems* in the Service Sector (IJISSS), 13(4), 62-87.

Aldossari, S., Mokhtar, U. A., & Abdul Ghani, A. T. (2023). Factor Influencing the Adoption of Big Data Analytics: A Systematic Literature and Experts Review. SAGE Open, 13(4), 1-25.

Aldosari, O. F., Hussain, I., & Malaibari, Z. (2023). Emerging trends of electrocatalytic technologies for renewable hydrogen energy from seawater: Recent advances, challenges, and techno-feasible assessment. *Journal of Energy Chemistry*, 80, 658-688.

Aldridge, I., & Avellaneda, M. (2021). Big Data Science in Finance (1st ed.). Wiley.

Al-Tit, A.A. (2020). E-commerce drivers and barriers and their impact on e-customer loyalty in small and medium-sized enterprises (SMEs). Business: *Theory and Practice*, 21(1), 146-157, doi: 10.3846/btp.2020.11612.

Ajzen, I. (1985) 'From intentions to actions: a theory of planned behaviour', in Action Control, pp.11–39, Springer, Berlin, Heidelberg.

Amini, M., & Jahanbakhsh Javid, N. (2023). A multi-perspective framework established on Diffusion of Innovation (DOI) theory and Technology, Organization and Environment (TOE) framework toward Supply Chain Management system based on cloud computing technology for small and medium enterprises, *International Journal of Information Technology and Innovation Adoption*, 11, 1217-1234.

Anwer, A.S. (2019). Towards better understanding of determinants logistical factors in SMEs for cloud ERP adoption in developing economies. *Business Process Management Journal*, 25(5), 887-907.

Asiaei, A. and Rahim, N.Z.A. (2019). A multifaceted framework for adoption of cloud computing in Malaysian SMEs. *Journal of Science and Technology Policy Management*, 10(3), 708-750.

Astuti, E.S., Sanawiri, B. and Iqbal, M. (2020). Attributes of innovation, digital technology and their impact on SME performance in Indonesia. *International Journal of Entrepreneurship*, 24(1), 1-14.

Awa, H.; Ukoha, O.; Igwe, S.R. (2017), Revisiting technology-organization-environment (T-O-E) theory for enriched applicability. Bottom Line 2017, 30, 2–22.

Bagozzi, R.P. (1981) 'Attitudes, intentions, and behaviour: a test of some key hypotheses', *Journal of Personality and Social Psychology*, Vol. 41, No. 4, p.607.

Bagozzi, R.P. (2007) 'The legacy of the technology acceptance model and a proposal for a paradigm shift', *Journal of the Association for Information Systems*, Vol. 8, No. 4, p.3.

Baig, M.I.; Shuib, L.; Yadegaridehkordi, E. A. (2021), Model for Decision-Makers' Adoption of Big Data in the Education Sector. *Sustainability*, 13, 13995.

Baron, R.M. and Kenny, D.A. (1986) 'The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations', *Journal of Personality and Social Psychology*, Vol. 51, No. 6, p.1173.

Barbosa, M. W., Vicente, A. de la C., Ladeira, M. B., & Oliveira, M. P. V. de. (2018). Managing supply chain resources with Big Data Analytics: a systematic review. *International Journal of Logistics Research and Applications*, 21(3), 177-200. https://doi.org/10.1080/13675567.2017.1369501

Benbasat, I. and Barki, H. (2007) 'Quo vadis TAM?', *Journal of the Association for Information Systems*, Vol. 8, No. 4, p.7.

Bian, Y., Kang, L. and Zhao, J.L. (2020), "Dual decision-making with discontinuance and acceptance of information technology: the case of cloud computing", *Internet Research*, Vol. 30 No. 5, pp. 1521-1546.

Bruhn, M., Schoenmueller, V. and Schäfer, D.B. (2012) 'Are social media replacing traditional media in terms of brand equity creation?', *Management Research Review,* Vol. 35, No. 9, pp.770–790.

Chatterjee, S. and Kar, A.K. (2020). Why do small and medium enterprises use social media marketing and what is the impact: empirical insights from India. *International Journal of Information Management*, 53, 102103

Chaudhary, K., & Alam, M. (2022). Big Data Analytics: Applications in Business and Marketing (1st ed.). Auerbach Publications. https://doi.org/10.1201/9781003307761

Chen, D.Q.; Preston, D.S.; Swink, M. How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *J. Manag. Inf. Syst*. 2015, 32, 4–39

Cheong, J.H. and Park, M.C. (2005) 'Mobile internet acceptance in Korea', *Internet Research*, Vol. 15, No. 2, pp.125–140.

Childers, T.L., Carr, C.L., Peck, J. and Carson, S. (2001) 'Hedonic and utilitarian motivations for online retail shopping behaviour', *Journal of Retailing*, Vol. 77, No. 4, pp.511–535.

Chun, H., Lee, H. and Kim, D. (2012) 'The integrated model of smartphone adoption: hedonic and utilitarian value perceptions of smartphones among Korean college students', *Cyberpsychology, Behaviour, and Social Networking*, Vol. 15, No. 9, pp.473–479.

Chung, J.E., Park, N., Wang, H., Fulk, J. and McLaughlin, M. (2010) 'Age differences in perceptions of online community participation among non-users: an extension of the technology acceptance model', *Computers in Human Behaviour*, Vol. 26, No. 6, pp.1674–1684.

Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS Quarterly*, Vol. 13, No. 3, pp.319–340.

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1992) 'Extrinsic and intrinsic motivation to use computers in the workplace 1', *Journal of Applied Social Psychology*, Vol. 22, No. 14, pp.1111–1132.

Davis, R. and Sajtos, L. (2008) 'Measuring consumer interactivity in response to campaigns coupling mobile and television media', *Journal of Advertising Research*, Vol. 48, No. 3, pp.375–391.

Dey, M. and Deb Nath, B. (2020). Factors affecting adoption of E-commerce in small and medium enterprises in India. *Journal of Test Engineering and Management*, 83, 11195-11202.

Dong, J.Q. and Yang, C.-H. (2020), "Business value of big data analytics: a systems-theoretic approach and empirical test", *Information & Management*, Vol. 57 No. 1, p. 103124.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., ... & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. International *journal of production economics*, 226, 107599.

Eagly, A.H. and Chaiken, S. (1993) The Psychology of Attitudes, Harcourt Brace Jovanovich College Publishers, Fort Worth, TX.

El-Haddadeh, R., Osmani, M., Hindi, N. and Fadlalla, A. (2021), "Value creation for realising the sustainable development goals: fostering organisational adoption of big data analytics", *Journal of Business Research*, Vol. 131, pp. 402-410.

Faridi, M.R. and Malik, A. (2020). Digital transformation in supply chain, challenges and opportunities in SMEs: a case study of Al-Rumman Pharma. Emerald Emerging Markets Case Studies, 10(1), 1-16.

Fishbein, M. and Ajzen, I. (1975) Belief, Attitude, and Behaviour: An Introduction to Theory and Research, Addison Wesley, Reading, Mass.

Garmaki, M., Gharib, R. K., & Boughzala, I. (2023). Big data analytics capability and contribution to firm performance: the mediating effect of organizational learning on firm performance. *Journal of Enterprise Information Management*, 36(5), 1161-1184.

Gaskin, J. (2012) 'Common method bias using common latent factor', Gaskination's Statistics [online] http://youtube.com/Gaskination (accessed 22 January 2012).

Ghafari, M., Ranjbarian, B. and Fathi, S. (2017) 'Developing a brand equity model for tourism destination', *International Journal of Business Innovation and Research*, Vol. 12, No. 4, pp.484–507.

Ghani, N. A., Hamid, S., Targio Hashem, I. A., & Ahmed, E. (2019). Social media big data analytics: A survey. *Computers in Human Behavior*, 101, 417-428. https://doi.org/10.1016/j.chb.2018.08.039

Giotopoulos, I., Kontolaimou, A., Korra, E. and Tsakanikas, A. (2017). What drives ICT adoption by SMEs? Evidence from a large-scale survey in Greece. *Journal of Business Research*, 81, 60-69.

Glaeser, E. L., Kominers, S. D., Luca, M., & Naik, N. (2018). Big data and big cities: The promises and limitations of improved measures of urban life. Economic Inquiry, 56(1), 114-137.

Goldstein, I., Spatt, C. S., & Ye, M. (2021). Big data in finance. The Review of Financial Studies, 34(7), 3213-3225. https://doi.org/10.1093/rfs/hhab038

Gökalp, M. O., Gökalp, E., Kayabay, K., Gökalp, S., Koçyiğit, A., & Eren, P. E. (2022). A process assessment model for big data analytics. *Computer Standards & Interfaces*, 80, 103585.

Ha, S. and Stoel, L. (2009) 'Consumer e-shopping acceptance: antecedents in a technology acceptance model', *Journal of Business Research*, Vol. 62, No. 5, pp.565–571.

Haenlein, M. and Kaplan, A.M. (2009) 'Flagship brand stores within virtual worlds: the impact of virtual store exposure on real-life attitude toward the brand and purchase intent', Recherche et Applications en Marketing, English Edition, Vol. 24, No. 3, pp.57–79.

Hameed, M.A.; Counsell, S. Assessing the influence of Environmental and CEO Characteristics for Adoption of Information Technology in Organizations. *J. Technol. Manag. Innov*. 2012, 7, 64–84

Hassan, M.U., Iqbal, Z. and Malik, M. (2019) 'Evaluation of individuals' behaviour patterns towards cellular network: an empirical study of Pakistan', *International Journal of Business Innovation and Research*, Vol. 18, No. 1, pp.64–86.

Hassan, S., Dhali, M., Zaman, F., & Tanveer, M. (2021). Big data and predictive analytics in healthcare in Bangladesh: regulatory challenges. *Heliyon,* 7(6). https://doi.org/10.1016/j.heliyon.2021.e07179

Hernández, Á. B., Perez, M. S., Gupta, S., & Muntés-Mulero, V. (2018). Using machine learning to optimize parallelism in big data applications. *Future Generation Computer Systems*, 86, 1076-1092.

Himeur, Y., Elnour, M., Fadli, F., Meskin, N., Petri, I., Rezgui, Y., ... & Amira, A. (2023). AI-big data analytics for building automation and management systems: a survey, actual challenges and future perspectives. *Artificial Intelligence Review*, 56(6), 4929-5021

Hong, L. C., & Ping, T. A. (2020). Investigating Determinants of Big Data Analytics Adoption in Malaysian SMEs.

Hossain, M. I., & Azam, M. S. (2023). The effects of technology, organization and environmental factors on small firm entry to electronic marketplace: a developing country perspective. *International Journal of Electronic Business*, 18(1), 77-107.

Hosseini, M. and Ghalamkari, A. (2018) 'Analysis social media-based brand communities and consumer behavior: a netnographic approach', International Journal of E-Business Research (IJEBR), Vol. 14, No. 1, pp.37–53.

Hwang, H.S. and Cho, J. (2018) 'Why Instagram? Intention to continue using Instagram among Korean college students', *Social Behaviour and Personality: An International Journal*, Vol. 46, No. 8, pp.1305–1315.

Ishikiriyama, C. S., & Gomes, C. F. S. (2019). Big data: A global overview. Big Data for the greater good, 35-50. Kapferer, J.N. and Bastien, V. (2012) The Luxury Strategy: Break the Rules of Marketing to Build Luxury Brands, Kogan Page Publishers, London.

Jackson, D., & Allen, C. (2024). Enablers, barriers and strategies for adopting new technology in accounting. International Journal of Accounting Information Systems, 52, 100666. Keller, K.L. (1993) 'Conceptualizing, measuring, and managing customer-based brand equity', *Journal of Marketing*, Vol. 57, No. 1, pp.1–22.

Jensen, M. H., Persson, J. S., & Nielsen, P. A. (2023). Measuring benefits from big data analytics projects: an action research study. *Information Systems and e-Business Management*, 21(2), 323-352.

Kaliraj, P., & Devi, T. (2022). Big Data Applications in Industry 4.0. In Big Data Applications in Industry 4.0 (1st ed.). CRC Press. https://doi.org/10.1201/9781003175889

Khayer, A., Talukder, M.S., Bao, Y. and Hossain, M.N. (2020), "Cloud computing adoption and its impact on SMEs' performance for cloud supported operations: a dual-stage analytical approach", *Technology in Society*, Vol. 60, p. 101225.

Kim, A.J. and Johnson, K.K. (2016) 'Power of consumers using social media: examining the influences of brand-related user-generated content on Facebook', *Computers in Human Behaviour*, Vol. 58, No. 5, pp.98–108.

Lautenbach, P., Johnston, K., & Adeniran-Ogundipe, T. (2017). Factors influencing business intelligence and analytics usage extent in South African organisations. *South African Journal of Business Management*, 48, 23–33.

Low, G.S. and Lamb Jr., C.W. (2000) 'The measurement and dimensionality of brand associations', Journal of Product & Brand Management, Vol. 9, No. 6, pp.350–370.

Lu, H.P. and Su, P.Y-J. (2009) 'Factors affecting purchase intention on mobile shopping web sites', *Internet Research*, Vol. 19, No. 4, pp.442–458.

Lutfi, A., Alrawad, M., Alsyouf, A., Almaiah, M. A., Al-Khasawneh, A., Al-Khasawneh, A. L., Alshira'h, A. F., Alshira'h, M. H., & Ibrahim, N. (2023). Drivers and impact of big data analytic adoption in the retail industry: A quantitative investigation applying structural equation modelling. *Journal of Retailing and Consumer Services*, 70, 103129.

Lutfi, A., Alshira'h, A. F., Alshirah, M. H., Al-Okaily, M., Alqudah, H., Saad, M., ...Abdelmaksoud, O. (2022). Antecedents and Impacts of Enterprise Resource Planning System Adoption among Jordanian SMEs. *Sustainability,* 14(6), 3508.
https://doi.org/10.3390/su14063508

Lutfi, A.A.; Idris, K.M.; Mohamad, R. The influence of technological, organizational and environmental factors on accounting information system usage among Jordanian small and medium-sized enterprises. *Int. J. Econ. Finance*. Issues 2016, 6, 240–248.

Lutfiani, L. S., Birgithri, A., & Queen, Z. (2024). Technological Aspects in the Era of Digital Transformation Leading to the Adoption of Big Data. *Startupreneur Business Digital (SABDA Journal)*, 3(1), 43-53.

Mao, E., Srite, M., Thatcher, J.B. and Yaprak, O. (2005) 'A research model for mobile phone service behaviors: empirical validation in the US and Turkey', *Journal of Global Information Technology Management*, Vol. 8, No. 4, pp.7–28.

Market and Market (2024), Big Data by Offering (Software (Big Data Analytics, Data Mining), Services), Business Function (Marketing & Sales, Finance & Accounting), Data Type (Structured and Semi-structured, Unstructured), Vertical and Region- Global Forecast to 2028 Big Data Market. https://www.marketsandmarkets.com/Market-Reports/big-data-market-1068.html?gad_source=1&gclid=Cj0KCQjwwYSwBhDcARIsAOyL0fiyatHWMZluXAjneFXsmY1-kZEq8EjiP5RXtC-owaL_r6GnCTK5zTMaAj1LEALw_wcB

Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. *International Journal of Information Management*, 54, 102190.

Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2023). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). Industrial Management & Data Systems, 123(1), 278-301.

Marr, B. (2022). Data strategy: how to profit from a world of big data, analytics, and artificial intelligence (2nd ed.). Kogan Page.

Martínez-Román, J. A., Gamero, J., Tamayo, J. A., & Delgado-González, L. (2020). Empirical analysis of organizational archetypes based on generation and adoption of knowledge and technologies. *Technovation*, 96, 102145.

M.M. Mariani, S. Nambisan Innovation analytics and digital innovation experimentation: the rise of research-driven online review platforms Technol. *Forecast. Soc. Chang*., 172 (2021), Article 121009

Msomi, M.P., Ngibe, M. and Nyide, C.J. (2019). Factors influencing the adoption of management accounting practices (MAPs) by manufacturing small and medium enterprises (SMEs) in Durban, KwaZulu-Natal. *International Journal of Entrepreneurship*, 23(4), 1-18.

Naeem, M., Jamal, T., Diaz-Martinez, J., Butt, S. A., Montesano, N., Tariq, M. I.,De-La-Hoz-Valdiris, E. (2022). Trends and future perspective challenges in big data. In Advances in intelligent data analysis and applications (pp. 309-325). Springer, Singapore.
https://doi.org/10.1007/978-981-16-5036-9_30

Nawi, N.B.C. and Al-Mamun, A. (2017) 'Customer satisfaction of online apparel businesses in Malaysia: point-purchase and post-purchase comparison', *International Journal of Business Innovation and Research*, Vol. 12, No. 3, pp.386–405.

Park, E.J., Kim, E.Y., Funches, V.M. and Foxx, W. (2012) 'Apparel product attributes, web browsing, and e-impulse buying on shopping websites', *Journal of Business Research*, Vol. 65, No. 11, pp.1583–1589.

Park, N. (2010) 'Adoption and use of computer-based voice over internet protocol phone service: toward an integrated model', *Journal of Communication*, Vol. 60, No. 1, pp.40–72.

Park, Y.W. and Shintaku, J. (2016) 'The replication process of a global localisation strategy: a case study of Korean firms', *International Journal of Business Innovation and Research*, Vol. 10, No. 1, pp.8–25.

Percy, L. and Rossiter, J.R. (1992) 'A model of brand awareness and brand attitude advertising strategies', *Psychology & Marketing*, Vol. 9, No. 4, pp.263–274.

Persaud, A. and Azhar, I. (2012) 'Innovative mobile marketing via smartphones: are consumers ready?', *Marketing Intelligence & Planning*, Vol. 30, No. 4, pp.418–443.

Piccarozzi, M., & Aquilani, B. (2022). The role of Big Data in the business challenge of Covid-19: a systematic literature review in managerial studies. *Procedia Computer Science*, 200, 1746-1755. https://doi.org/10.1016/j.procs.2022.01.375

Pijpers, G.G. and van Montfort, K. (2005) 'An investigation of factors that influence senior executives to accept innovations in information technology', *International Journal of Management*, Vol. 22, No. 4, p.542.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003) 'Common method biases in behavioural research: a critical review of the literature and recommended remedies', *Journal of Applied Psychology*, Vol. 88, No. 5, p.879.

Pongjit, C. and Chiaravutthi, Y. (2018) 'Brand and brand origin valuations: a case of the electrical appliance market in Thailand', *International Journal of Business Innovation and Research*, Vol. 17, No. 2, pp.187–209.

Rajagopal, N.A. and Rajagopal, A. (2018) 'Brand literacy and knowledge transfer process: analysis of purchase intentions among consumers in Mexico', *International Journal of Business Innovation and Research*, Vol. 16, No. 3, pp.302–323.

Rauniar, R., Rawski, G., Yang, J. and Johnson, B. (2014) 'Technology acceptance model (TAM) and social media usage: an empirical study on Facebook', *Journal of Enterprise Information Management*, Vol. 27, No. 1, pp.6–30.

Raut, R. D., Mangla, S. K., Narwane, V. S., Gardas, B. B., Priyadarshinee, P., & Narkhede, B. E. (2019). Linking big data analytics and operational sustainability practices for sustainable business management. *Journal of Cleaner Production*, 224, 10-24. https://doi.org/10.1016/j.jclepro.2019.03.181

Reyes-Mercado, P., Karthik, M., Mishra, R.K. and Rajagopal, N.A. (2017) 'Drivers of consumer attitudes towards online shopping in the Indian market: analysis through an extended TAM model', *International Journal of Business Innovation and Research*, Vol. 13, No. 3, pp.326–343.

Raguseo, E. (2018). Big data technologies: An empirical investigation on their adoption, benefits and risks for companies. *International Journal of Information Management*, 38(1), 187-195.

Rivai, H.A. and Fernando, Y. (2019) 'Intention to use the internet of micro-size enterprises: evidence from the biggest emerging market in Southeast Asia', *International Journal of Business Innovation and Research*, Vol. 18, No. 1, pp.47–63.

Rossiter, J.R. and Percy, L. (1987) Advertising and Promotion Management, McGraw-Hill Book Company, New York.

Saka, A.B. and Chan, D.W. (2020). Profound barriers to building information modelling (BIM) adoption in construction small and medium-sized enterprises (SMEs): An interpretive structural modelling approach. *Construction Innovation*, 20(2), 261-284.

Salwani, M.I.; Marthandan, G.; Norzaidi, M.D.; Chong, S.C. E-commerce usage and business performance in the Malaysian tourism sector: Empirical analysis. *Inf. Manag. Comput. Secur.* 2009, 17, 166–185

Sarifah, M.F. (2019) 'Naive Bayes algorithm performance for smartphone sentiment analysis in social media', *International Journal Artificial Intelligent and Informatics*, Vol. 1, No. 2, pp.76–81.

Sethuraman, P. and Thanigan, J. (2019) 'An empirical study on consumer attitude and intention towards online shopping', *International Journal of Business Innovation and Research, Vol*. 18, No. 2, pp.145–166.

Shahzad, A., Chin, H.K., Altaf, M. and Bajwa, F.A. (2020). Malaysian SME's performance and the use of e-commerce: A multi-group analysis of click-and-mortar and pure-play e-retailers. Pakistan Journal of Commerce and Social Sciences (PJCSS), 14(1), 1-33.

Sharma, B.K. and Bhatt, V.K. (2018) 'Impact of social media on consumer buying behaviour – a descriptive study on tam model', *i-Manager's Journal on Management*, Vol. 13, No. 1, p.34.

Shimp, T.A. (1981) 'Attitude toward the ad as a mediator of consumer brand choice', *Journal of Advertising*, Vol. 10, No. 2, pp.9–48.

Shukla, P. (2011) 'Impact of interpersonal influences, brand origin and brand image on luxury purchase intentions: measuring interfunctional interactions and a cross-national comparison', *Journal of World Business*, Vol. 46, No. 2, pp.242–252.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, 70, 263-286. https://doi.org/10.1016/j.jbusres.2016.08.001

Sivarajah, U., Kumar, S., Kumar, V., Chatterjee, S., & Li, J. (2024). A study on big data analytics and innovation: From technological and business cycle perspectives. *Technological Forecasting and Social Change*, 202, 123328.

Spears, N. and Singh, S.N. (2004) 'Measuring attitude toward the brand and purchase intentions', *Journal of Current Issues & Research in Advertising*, Vol. 26, No. 2, pp.53–66.

Sundaram, A. and Radha, P. (2019) 'Social media security and privacy protection concerning youths. 'How to be safe, secure and social'', *International Journal of Business Innovation and Research*, Vol. 18, No. 4, pp.453–471.

Sun, N., Zhang, J., Rimba, P., Gao, S., Zhang, L. Y., & Xiang, Y. (2018). Data-Driven Cybersecurity Incident Prediction: A Survey. IEEE Communications Surveys & Tutorials, 21(2), 1744-1772.https://doi.org/10.1109/COMST.2018.2885561

Talaoui, Y., Kohtamäki, M., Ranta, M., & Paroutis, S. (2023). Recovering the divide: A review of the big data analytics-strategy relationship. Long Range Planning, 102290.https://doi.org/10.1016/j.lrp.2022.102290

The Edge Malaysia (2024), https://theedgemalaysia.com/article/mdecs-commissioned-study-shows-malaysias-big-data-analytics-market-expected-grow-us19b-2025

Urus, S. T., Othman, I. W., Rasit, Z. A., Bakar, N. A., & Nazri, S. N. F. S. M. (2023) Beyond the Hype of Big Data Analytics Deployment: Conceptualization and Challenges Epistemology. *Business and Economic Research*, 13(2), 74-111.

Venkatesh, V. and Davis, F.D. (1996) 'A model of the antecedents of perceived ease of use: development and test', *Decision Sciences*, Vol. 27, No. 3, pp.451–481.

Villarejo-Ramos, A.F. and Sanchez-Franco, M.J. (2005) 'The impact of marketing communication and price promotion on brand equity', *Journal of Brand Managemen*t, Vol. 12, No. 6, pp.431–444.

Vrchota, J., Frantíková, Z., & Vlčková, M. (2019). Why some SME's in the Czech Republic adopt telework and others not?. European Countryside, 11(4), 599-615.

Wahab, S. N., Hamzah, M. I., Sayuti, N. M., Lee, W. C., & Tan, S. Y. (2021). Big data analytics adoption: an empirical study in the Malaysian warehousing sector. *International Journal of Logistics Systems and Management*, 40(1), 121-144. https://doi.org/10.1504/IJLSM.2021.117703

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of business research*, 70, 356-365.

Wang, X., Yang, Z. and Liu, N.R. (2009) 'The impacts of brand personality and congruity on purchase intention: evidence from the Chinese Mainland's automobile market', *Journal of Global Marketing*, Vol. 22, No. 3, pp.199–215.

Waqar, J., & Paracha, O. S. (2023). Antecedents of big data analytics (BDA) adoption in private firms: a sequential explanatory approach. foresight.

Wessels, T., & Jokonya, O. (2022). Factors affecting the adoption of big data as a service in SMEs. *Procedia Computer Science*, 196, 332-339.

Yang, K. (2012) 'Consumer technology traits in determining mobile shopping adoption: an application of the extended theory of planned behavior', *Journal of Retailing and Consumer Services*, Vol. 19, No. 5, pp.484–491.

Yang, K.C. (2005) 'Exploring factors affecting the adoption of mobile commerce in Singapore', *Telematics and informatics*, Vol. 22, No. 3, pp.257–277.

Yadegaridehkordi, E.; Nilashi, M.; Shuib, L.; Nasir, M.H.N.B.M.; Asadi, S.; Samad, S.; Awang, N.F. The impact of big data on firm performance in hotel industry. *Electron. Commer. Res. Appl.* 2020, 40, 10.

Yoo, B., Donthu, N. and Lee, S. (2000) 'An examination of selected marketing mix elements and brand equity', *Journal of the Academy of Marketing Science*, Vol. 28, No. 2, pp.195–211.

Youssef, M. A. E. A., Eid, R., & Agag, G. (2022). Cross-national differences in big data analytics adoption in the retail industry. *Journal of Retailing and Consumer Services*, 64, 102827.

Zamani, S. Z. (2022). Small and Medium Enterprises (SMEs) facing an evolving technological era: a systematic literature review on the adoption of technologies in SMEs. *European Journal of Innovation Management*, 25(6), 735-757.