THE IMPACT OF TECHNOLOGY, ORGANIZATION, ENVIRONMENT TOWARDS ORGANIZATIONAL PERFORMANCE FOR BIG DATA ADOPTION IN MALAYSIA DIGITAL STATUS COMPANIES

By

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ABSTRACT

The rapid advancement of technology, driven by digitalization and Industry 4.0, has significantly transformed the global business landscape. This transformation has created both opportunities and challenges in managing the exponential growth of data, often referred to as Big Data. Despite various initiatives launched since 2014, the adoption of Big Data technologies in Malaysia remains low, with a significant gap in data expertise. This study explores the moderating role of training in the relationship between data quality management, data security, ease of use, and top management support, particularly within Malaysia's Global Business Services (GBS) sector. Data were collected from companies with Malaysia Digital Status within the GBS cluster, utilizing the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV) as the theoretical foundation. An online questionnaire distributed to companies in the GBS cluster resulted in 272 responses through simple random sampling. Due to a low response rate, convenience sampling was subsequently employed to ensure a sufficient sample size. Hypothesis testing was conducted using Smart PLS 4.1.0.0. The findings indicate that data quality management, ease of use, and top management support significantly influence organizational performance, while data security did not show a significant impact. Furthermore, training was found to significantly moderate the relationship between ease of use and organizational performance, although it did not significantly moderate the relationships between other variables and organizational performance. Failure to adopt Big Data can result in inaccurate decisions, reduced customer satisfaction, and the loss of competitive advantage. This study contributes to both theoretical and practical understanding by addressing a critical gap in Big Data adoption, emphasizing training as a key factor in improving ease of use and enhancing adoption outcomes, particularly in the Malaysian GBS sector. It also offers actionable insights for organizations aiming to leverage Big Data to enhance performance and competitiveness.

Keywords: Big data adoption (BDA); Organizational performance; Technology-Organization-Environment (TOE) Framework; Resource-Based View (RBV); Global Business Services (GBS)

ABSTRAK

Perkembangan pesat teknologi didorong oleh digitalisasi dan Industri 4.0, telah mengubah secara signifikan landskap perniagaan global. Transformasi ini telah mencipta peluang dan cabaran dalam menguruskan pertumbuhan data secara eksponen, yang sering dirujuk sebagai Data Raya. Walaupun pelbagai inisiatif telah dilancarkan sejak tahun 2014, kadar penerimaan teknologi Data Raya di Malaysia masih rendah, dengan jurang ketara dalam kepakaran data. Kajian ini meneliti peranan pengantaraan latihan dalam hubungan antara pengurusan kualiti data, keselamatan data, kemudahan penggunaan, dan sokongan pengurusan atasan, terutama dalam sektor Perkhidmatan Perniagaan Global (GBS) di Malaysia. Data dikumpulkan daripada syarikat yang berstatus Digital Malaysia dalam kluster GBS, menggunakan Kerangka Teknologi-Organisasi-Persekitaran (TOE) dan Pandangan Berasaskan Sumber (RBV) sebagai asas teorinya. Data dikumpulkan melalui soal selidik dalam talian yang diedarkan kepada syarikat dalam kluster GBS, menghasilkan 272 respons yang diperoleh melalui pensampelan rawak mudah. Disebabkan kadar respons yang rendah, pensampelan kemudahan kemudiannya digunakan untuk memastikan saiz sampel yang mencukupi. Ujian hipotesis dilakukan menggunakan Smart PLS 4.1.0.0. Dapatan kajian menunjukkan bahawa pengurusan kualiti data, kemudahan penggunaan, dan sokongan pengurusan atasan mempunyai pengaruh yang signifikan terhadap prestasi organisasi, manakala keselamatan data tidak menunjukkan kesan yang signifikan. Selain itu, aspek latihan didapati memoderasi hubungan antara kemudahan penggunaan dan prestasi organisasi secara signifikan, walaupun ia tidak memoderasi secara signifikan hubungan antara pembolehubah lain dengan prestasi organisasi. Kegagalan dalam penyerapan Data Raya boleh membawa kepada keputusan yang tidak tepat, menjejaskan kepuasan pelanggan, dan mengakibatkan kehilangan kelebihan daya saing. Kajian ini meningkatkan pemahaman teoritis dan praktikal dengan menangani jurang kritikal dalam memahami bagaimana latihan memoderasi hubungan antara pembolehubah dan prestasi organisasi, khususnya dalam sektor GBS di Malaysia. Pada masa yang sama, kajian ini menyediakan pandangan yang boleh diambil tindakan untuk membimbing organisasi dalam memanfaatkan Data Raya bagi meningkatkan prestasi dan daya saing.

Kata Kunci: Penyerapan data raya; Prestasi organisasi; Kerangka Teknologi-Organisasi-Persekitaran (TOE); Pandangan Berasaskan Sumber (RBV); Perkhidmatan Perniagaan Global (GBS)

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
BDA	Big Data Adoption
BI	Business Intelligence
CAGR	Compound Annual Growth Rate
DBMS	Database Management System
GBS	Global Business Services
HR	Human Resource
HRDF	Human Resource Development Fund
IDC	International Data Corporation
IMS	Information Management System
IoT	Internet of Things
MD	Malaysia Digital
ML	Machine Leaning
MDEC	Malaysia Digital Economy Corporation
MSC	Multimedia Super Corridor
PEOU	Perceived Ease of Use
RBV	Resource Based View
RFID	Radio Frequency Identification Design
SDG	Sustainable Development Growth
TOE	Technology-Organization-Environment

CHAPTER 1

INTRODUCTION

1.1 Introduction

The rapid growth of digital technologies, as well as the rising ability to capture and store enormous amounts of data, has resulted in the term "Big Data." Businesses in Industry 4.0 are embracing emerging technology tools and solutions such as artificial intelligence (AI), the Internet of Things (IoT), cloud computing, and cyber-physical systems to construct integrated networks that translate data into actionable insights. These technologies enable companies to make more informed decisions, optimize operations, and improve overall performance (Kamarulzaman & Hassan, 2019; Mateev, 2020). The capacity to use Big Data has emerged as a critical aspect in achieving competitive advantage, allowing companies to obtain deeper insights, optimize processes, and adapt quickly to changing market dynamics. As a result, digital transformation is sweeping across industries worldwide, altering business models and increasing operational efficiencies (Ajah & Nweke, 2019).

Malaysia, like many other rising economies, is attempting to capitalise on the digital transformation in order to increase economic growth and maintain global competitiveness. The use of digital technologies such as cloud computing, artificial intelligence, and big data analytics has drastically changed how Malaysian businesses function, giving them the tools they need to make data-driven choices and improve performance. However, despite global advancements, the use of Big Data technology in Malaysia is still limited. According to the National Business Digital Adoption Index report (2022), 64% of Malaysian businesses have yet to embrace any type of digital technology, with 61% expressing misgivings about doing so. Furthermore, 60% of businesses continue to use traditional data collection tools, drastically limiting their analytical capabilities and impeding their capacity to extract value from data. This situation emphasizes the crucial necessity for Malaysian businesses to speed their digital transformation initiatives to avoid falling behind regional competitors (MDEC, 2022a).

In addition to low adoption rates, Malaysia has a substantial talent gap in the field of Big Data. According to studies, there is a significant shortage of experienced data experts, which not only slows adoption but also has an impact on the quality and efficiency of Big Data initiatives (Hafizal Ishak et al., 2023; Sumathi et al., 2019). The Malaysia Digital Economy Corporation (MDEC) planned to train 20,000 data professionals by 2020, including 2,000 data scientists. However, the demand for data professionals continues to outweigh the supply, resulting in a talent bottleneck that stymies Malaysia's progress toward digital maturity (K. Singh, 2018). This talent gap is compounded by the rapid growth of digital job opportunities, which have nearly tripled from 19,000 in June 2020 to 56,000 by April 2021 (Oi, 2022). The mismatch between digital growth targets and the availability of competent talent poses a significant barrier to Malaysia's digital transformation goals, emphasizing the crucial need for focused upskilling and reskilling projects (Randstad, 2022).

Slow adoption of Big Data technology, as well as a skilled workforce scarcity, are major impediments stopping Malaysian organizations from fully enjoying the benefits of digital transformation. Despite many government initiatives, like the Malaysia

Digital Economy Blueprint and the Eleventh Malaysia Plan, businesses struggle to integrate advanced analytics tools due to implementation complexity and a lack of strategic alignment (MyGovernment, 2018). Furthermore, established organizational practices, reluctance to change, and insufficient data governance frameworks impede the efficient use of Big Data technologies (M. Johnson et al., 2021; Shanmugam et al., 2023).

The ongoing deficiencies in data quality management (Al-madhrahi et al., 2022; Arunachalam & Kumar, 2018; Nilashi et al., 2023; Shanmugam et al., 2023; Solana-González et al., 2021; Taleb et al., 2021), data security (Asiri et al., 2024; Kim & Cho, 2018; Mangla et al., 2020a; Marr, 2018; Salleh & Janczewski, 2019; Thanabalan et al., 2024), ease of use (Abdullah Sani et al., 2021; Ajah & Nweke, 2019; Al-madhrahi et al., 2022; Amalina et al., 2019; Dias et al., 2021; Smith, 2023), and support from top management (Hafizal Ishak et al., 2023; Hamzah et al., 2020; Reyes-Veras et al., 2021; Shahbaz et al., 2019; Wook et al., 2021) hamper the adoption process.

Poor data quality, for example, reduces the accuracy and dependability of insights, resulting in incorrect decision-making and operational inefficiencies (Onyeabor & Ta'a, 2018; Shanmugam et al., 2023). Data security concerns, on the other hand, provide significant environmental challenges as companies face growing risks of data breaches and regulatory noncompliance (Anwar et al., 2021). Furthermore, the difficulty of employing Big Data tools frequently discourages employees from fully utilizing these technologies, while poor support from top management can result in a lack of strategic focus and resource allocation (Hadidi & Power, 2020; Tabesh et al., 2019).

Several studies have attempted to determine the relationship between important drivers such as data quality, data security, ease of use, and top management support in impacting Big Data adoption and organizational (Hashim et al., 2021; M. T. Huynh et al., 2023). However, the results are sometimes conflicting, with some research indicating a large impact on performance and others indicating a minor effect (Elbanna & Newman, 2022). For example, Ghasemaghaei and Calic, (2019) discovered no direct association between data quality and organizational performance, claiming that other factors such as leadership and strategic alignment are more important in predicting success. Similarly, Parulian et al. (2023) observed that, while ease of use is vital for initial adoption, it does not necessarily transfer into improved performance, particularly when underlying organizational challenges like data integration and worker readiness are not addressed.

Several strategic initiatives have shaped Malaysia's digital transformation journey, notably the National Big Data Analytics Framework and the Malaysia Digital Economy Blueprint, which aim to position the country as a regional leader (Azman et al., 2021). Companies holding Malaysia Digital Status, formerly known as MSC Status, are critical to this initiative, receiving incentives and support to advance the country's digital agenda. These businesses play an important role in pushing digital adoption and innovation, making them excellent case studies for studying the influence of Big Data technologies on performance (MITI, 2023). However, the unique issues these organizations confront, such as reconciling global operational needs with local regulatory obligations, requires a more nuanced approach to Big Data adoption.

This study uses the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV) theory to investigate how major drivers affect Big Data adoption and its impact on organizational performance. The TOE framework identifies three dimensions; technology, organization, and environment as essential elements influencing technology adoption decisions. The RBV hypothesis, on the other hand, highlights the strategic importance of internal resources like training in maintaining competitive advantage (Barney, 1991a). Training is added as a moderating variable to better understand how it influences the impact of data quality management, data security, ease of use, and top management support on organizational performance.

1.1.1 Gaps in the Area of Knowledge

This study fills various research gaps in the existing literature specified as follows:

Research gap 1: Inconsistent findings of the Determinants of Organizational Performance in Big Data Adoption

The literature on big data adoption reveals conflicting results about the impact of key determinants on organizational performance, particularly in the areas of data quality management, data security, ease of use, top management support, and training. These inconsistencies are highlighted by varying perspectives on how each determinant affects the overall success of big data initiatives.

The impact of numerous determinants on organizational performance in big data adoption yields mixed results, leading to ambiguity in the literature. Some researchers have found that data quality management significantly improves decision-making and operational efficiency (Barney, 1991a; Wook et al., 2021), whereas others argue that its influence is minor and easily manipulated, reducing its practical relevance (Ali, 2023; Eng & Lin, 2012). Similarly, data security is regarded as critical for establishing trust and compliance, which contributes to performance improvement (Hamzah et al., 2020; Harun et al., 2022), but other research indicates that data security concerns do not always impede adoption or have a direct impact on performance outcomes (Ghasemaghaei, 2020; Yadegaridehkordi et al., 2018). While initial studies highlight ease of use's role in facilitating adoption and user satisfaction (Al-Rahmi et al., 2019; Soon et al., 2016), some researchers argue that ease of use alone can sometimes have a minimal or negative effect, especially if it becomes outdated due to a lack of continuous support or adaptation to new skills (Akter et al., 2016; Mahmood et al., 2023). Top management support exhibits similar inconsistencies; while it is frequently cited as a key driver for aligning strategies and supporting technology initiatives (Hashim et al., 2021; Ijab et al., 2019), its direct impact on performance is questioned, with some studies indicating limited or indirect influence unless combined with other organizational factors. These disparities underscore the necessity for a comprehensive evaluation that incorporates these drivers in order to appropriately measure their combined impact on big data adoption and organizational performance.

Research gap 2: Limited Exploration of Combined Theory and Determinants in Assessing Big Data Adoption Impact on Organizational Performance

While several studies have looked into individual determinants of big data adoption, such as data quality management, data security, ease of use, and top management support, there has been little integration of these factors into a comprehensive framework to assess their combined impact on organizational performance. Existing research frequently considers these variables separately or with different variables, limiting the understanding of how they interact to determine big data adoption outcomes (Anawar et al., 2022; Hadidi & Power, 2020; Shanmugam et al., 2023). The fragmented treatment of various drivers leads in a lack of a coherent understanding of how businesses should handle these elements concurrently to reach peak performance.

Furthermore, theoretical frameworks are not fully integrated to describe the complexities of Big Data adoption processes. Most studies use either the Technology-Organization-Environment (TOE) framework or the Resource-Based View (RBV) theory in isolation, limiting their ability to assess the internal and external factors that drive Big Data success (Hashim et al., 2021; Lutfi, Al-Khasawneh, et al., 2022). The lack of a cohesive theoretical approach limits our knowledge of how multiple determinants interact and influence adoption outcomes.

This gap highlights the need for a more comprehensive approach that takes into account the complex interactions between various variables, resulting in a clearer picture of their cumulative impact on performance. Addressing this gap would help to create a stronger theoretical framework that appropriately depicts the varied character of big data adoption, particularly in various organizational settings like Malaysia.

Research gap 3: Lack of Empirical Studies on Big Data Adoption in Malaysia Digital Status Companies

Despite the increased interest in big data adoption, there has been little empirical study on Malaysian companies with Malaysia Digital Status (MD). Many studies look at big data adoption in developed economies or at the organizational level, but they fail to understand the specific problems and opportunities encountered by Malaysian companies (Reza et al., 2021; Zian et al., 2024b). These businesses have distinct characteristics that required specific methods for successful big data implementation, particularly in terms of balancing global operational priorities and local regulatory obligations.

This gap highlights the need for study big data adoption among Malaysia's Malaysia Digital Status companies. Addressing this gap will provide novelty insights into the particular strategic and operational issues of these companies, helping to drive policy decisions and establish tailored strategies for digital transformation in the Malaysian environment.

Research gap 4: Underexplore the Role of Training as a Moderator in Big Data Adoption Outcomes

Training has been identified as a critical enabler of technology adoption, especially in swiftly evolving fields such as big data. However, most studies have indicated training as future studies instead of examining training as part of the studies of big data adoption and organizational performance (Akter et al., 2016; Q. U. A. Mahmood et al., 2023; Zian et al., 2024b). This oversight is crucial since the effectiveness of training is determined by its connection with the specific demands of data experts and the continually changing technology landscape.

This gap highlights the importance of empirically validating training's moderating influence in order to establish how it may enhance or moderate the impact of other determinants on big data adoption outcomes. Such research would provide practical guidance for developing training programs that are both relevant and capable of supporting long-term performance increases in businesses navigating the complexity of big data adoption.

This study will contribute to both theoretical and practical areas by addressing current gaps in the literature and giving actionable insights for Malaysian companies wanting to harness big data technology to improve their performance and competitiveness in the era of Industry 4.0.

The primary goal of this research is to investigate the relationship between data quality management, data security, ease of use, and top management support in Big Data adoption and their impact on organizational performance. Furthermore, the study intends to evaluate the moderating effect of training on these correlations. This study, by combining the TOE and RBV theories, contributes to a better understanding of the dynamics impacting Big Data adoption in Malaysian Digital Status organizations. The findings provide actionable insights for company leaders and governments seeking to strengthen digital strategy, optimize resource allocation, and boost overall competitiveness in the era of Industry 4.0.

In summary, this study offers substantial theoretical and practical contributions to the field of Big Data adoption. From a theoretical perspective, the research addresses a critical gap by introducing new integrated framework by integrating the Technology-

Organization-Environment (TOE) framework and Resource-Based View (RBV) theory into a single, comprehensive model that explains how external factors (technology, organization, and environment) and internal resources (training) jointly influence Big Data adoption outcomes. This combined approach enriches existing models by introducing training as a moderating variable, providing a novel perspective on how internal resources can enhance or mitigate the impact of external factors on organizational performance.

From a practical contribution, the study offers actionable insights for Malaysia Digital Status companies, particularly within the Global Business Services (GBS) sector, to optimize their Big Data strategies. By focusing on key determinants; data quality management, data security, ease of use, and top management support, the research provides a clear framework for business leaders to identify and address critical barriers to successful digital transformation. Furthermore, the study highlights the pivotal role of targeted training programs in bridging skill gaps and enhancing the effectiveness of Big Data initiatives. This emphasis on training as a moderating factor not only highlights its importance in overcoming challenges related to ease of use and data security but also equips organizations with practical guidance for workforce development.

Overall, this study significantly advances both theoretical frameworks and practical contribution by offering a robust model for understanding the dynamics of Big Data adoption. It contributes to the broader literature on digital transformation and provides a validated roadmap for companies and policymakers aiming to leverage Big Data to achieve sustainable performance improvements in the rapidly evolving digital economy.

1.2 Background of Study

As advancements in technology affect the way data is used, the effect goes beyond organizational boundaries, triggering a worldwide wave of digital transformation that is felt strongly in both developed and emerging economies. This transformation is affecting businesses in both established and emerging economies, like Malaysia, where businesses are progressively adopting digital technologies to improve operational efficiency and gain a competitive advantage (MDEC, 2022). The incorporation of digital technologies such as cloud computing, artificial intelligence, and big data analytics has transformed how businesses function, allowing them to use data to make better decisions and increase performance (McKinsey Digital, 2023).

Organizations are increasingly using big data technology to drive their strategic goals, in line with Industry 4.0 principles. Big data adoption, in particular, plays an important role in corporate decision-making by translating raw data into actionable insights (Ajah & Nweke, 2019; M. T. Huynh et al., 2023). However, implementing big data solution is a complex process that necessitates addressing a variety of technical, organizational, and environmental concerns. The organization's ability to control data quality (Shanmugam et al., 2023; Onyeabor & Ta'a, 2018), data security (Anawar et al., 2022), ease of use (Hadidi & Power, 2020), and top management support (Elbanna & Newman, 2022; Tabesh et al., 2019), all have an impact on the success of this adoption process (Davenport et al., 2010; Davenport & Harris, 2009; Maroufkhani et al., 2019).

Several research on technology adoption have stressed the necessity of data quality management. Poor data quality, defined as incomplete, inaccurate, or inconsistent data, can weaken the effectiveness of big data analytics and impede corporate performance (Shanmugam et al., 2023). Ensuring high-quality data is critical for companies seeking accurate insights and making educated decisions (Onyeabor & Ta'a, 2018). Contrary, other studies show that other factors, including as leadership, strategic alignment, and staff competence, are more essential in predicting organizational outcomes (Ghasemaghaei & Calic, 2019; Ali, 2023).

Similarly, data security has arisen as a major worry in the deployment of big data technology. As organizations rely more on data-driven operations, data confidentiality, integrity, and availability become critical for assuring operational continuity and protecting sensitive information (Anawar et al., 2022). While some research indicates that data security has a direct impact on organizational performance, other studies suggest that the relationship may be less significant, especially in environments where organizations prioritize operational efficiency over stringent security measures (T. N. Huynh et al., 2023).

Another important aspect that influences big data analytics adoption is ease of use. Organizations are more likely to adopt intuitive and user-friendly technologies, particularly in the early stages of adoption (Hadidi & Power, 2020). When employees can readily connect with big data platforms, they are better able to produce insights and make data-driven decisions, which improves overall organizational performance. However, while ease of use encourages early acceptance, it is not always adequate for long-term success. Other elements, such as training, data quality, and management support, are typically more important in guaranteeing long-term performance increases (Parulian et al., 2023).

Top management support is also critical to ensuring the successful use of big data technology. Top management's commitment to providing the necessary resources, and strategic direction is frequently the deciding element in whether a company can successfully incorporate and integrate big data analytics into its operations (Tabesh et al., 2019; Elbanna & Newman, 2022) . Organizations may struggle to realize the full potential of these technologies unless they have strong leadership and top-level backing. Futhermore, the roles and responsibilities of managers in implementing big data strategies have been debated (Tabesh et al., 2019), with other factors such as data integration, and operational capabilities are often more significant in sustaining long-term performance (T. N. Huynh et al., 2023).

Furthermore, training; such as lack on continuous learning contribute to the obstructive elements that restrict the growth of big data adoption. At the same time, training can quickly become outdated due to a lack of ongoing support and skill modifications (Akter et al., 2016; Mahmood et al., 2023). Furthermore, there is limited research on Big Data adoption in Malaysia that evaluates training environment (Al-Rahmi et al., 2019; Baharuden et al., 2019a, 2019b; Harun et al., 2022; Kamarulzaman & Hassan, 2019a; Lutfi, Al-Khasawneh, et al., 2022).

While a lack of continual learning and support hamper the expansion of big data adoption, these issues are worsened by the quick rate of technical change. As companies embrace more agile techniques to react to changing technologies, the demand for timely and relevant training grows even stronger. Organizations may struggle to remain competitive if training is not properly aligned with the rapidly changing technology world. The technology adoption process is thus critical not just for picking innovations, but also for ensuring that businesses are appropriately equipped for the future (Weng, 2020).

Technology adoption is critical at the early stages of selecting suitable rapid-changing technological innovations for an individual or organization. In fact, the adoption of big data and organizational change agility are interconnected where organizations are shifting from traditional change management to more agile approaches to keep pace with rapidly evolving technology and competition (Majnoor & Vinayagam, 2023).

However, deploying new technology demands significant investment and may not yield the best outcomes if the intended users do not completely embrace the adoption. Furthermore, unclear understanding of the benefits of technology, a lack of technical and management skills, technical and technological integration challenges, incompetence resources, and a lack of support to start and implement technology are among the reported barriers to technology adoption (Chong et al., 2023; Tabesh et al., 2019; McKinsey, 2018). With all of the benefits and obstacles of big data adoption, as well as the previous technology adoption process, there is a need to investigate the determinants of the adoption in order to gain a competitive advantage, make better decisions, and expand operational efficiency.

1.2.1 Importance of Big Data

The term “Big Data” encompasses to the tremendous expansion of datasets in terms of size, diversity, and complexity, making them difficult to process with traditional methods and requiring new techniques to extract insights. According to Oxford dictionary (2013), Big Data refers to “sets of information (dataset) that are too large or too complex to handle, difficult to analyze using standard methods”. The complexities of Big Data make it nearly impossible to process using conventional methods, emphasizing the need for specialized computational algorithms. Advanced techniques are essential for deriving meaningful insights from Big Data, which is often analyzed using computational algorithms to uncover patterns and associations (Kaisler et al., 2014; Rehman & Batool, 2015; Bousdekis et al., 2021; Hamza et al., 2022). It can’t even be processed using traditional tools due to the overloaded of data and consequently led to so much complexity (Fan, 2013; Sridhar & Dharmaji, 2013; Ajah & Nweke, 2019; Shahad Alghamdi et al., 2023).

The sensation of the term “Big Data” was further popularized by Roger Magoulas, who introduced it through O’Reilly Media in 2010 (Magoulas, 2010). Magoulas’s contributions brought greater attention to the challenges and opportunities presented by Big Data, marking a pivotal moment in its conceptual evolution. However, as Id et al. (2020) noted, the rise of Big Data has resulted in conceptual ambiguity, with researchers expressing frustration over inconsistent interpretations that impede efforts to define the term using a common standard. According to Beyer and Laney (2012), De Mauro et al. (2016), Favaretto et al. (2020), and Volk et al. (2022), Big Data is still conceptually unclear, with words such as "Data Analytics" frequently used interchangeably, generating misunderstanding in both academia and industry. The interdisciplinary nature of Big Data research makes it more difficult to define its specific extent and build a common understanding. This emphasizes the significance of explicitly defining the field in order to encourage a thorough understanding of Big Data's scope and influence (Günther et al., 2017; Vassakis et al., 2018; Baharuden et al., 2019a).

While the conceptual ambiguity of Big Data remains a challenge, efforts to define its characteristics have evolved over time. In 2001, Doug Laney, a Gartner analyst, introduced the foundational of 3Vs to describe Big Data: Volume, Variety, and Velocity. And the Vs has evolved since then, from 3Vs to 5Vs (Volume, Variety, Velocity, Veracity and Value) as what stated by Fallis (2013) and Jasim Hadi et al. (2015). In 2021, Saeed and Husamaldin introduced 10Vs which are Volume, Velocity, Variety, Veracity, Value, Validity, Volatility, Variability, Visualization, and Vulnerability.

Nonetheless, the growing nature of technology continues to push the boundaries of what defines Big Data, provoking continuous debates about its problems and the efficacy of adopting analytics to improve organizational performance and competitive advantage. Despite the ongoing debates surrounding the precise definition of Big Data, the value derived from Big Data is significantly important to warrant focus on its practical benefits. Big data can be metaphorically described as the soil, with data analytics representing the plants that grow from this soil. Therefore, the exploration and advantages generated by Big Data far outweigh the concerns about its definition.

Building on this, Davenport (2019) emphasizes the revolutionary impact of data analytics, demonstrating asserted the era of analytics as a transformative phase in which organizations increasingly rely on data analytics to drive strategic decision-making, operational efficiency, and competitive advantage. This period highlights the need for technology infrastructure, competent workers, and supportive government to efficiently leverage Big Data. Davenport's work demonstrates how the capacity to analyze huge datasets enables companies to discover useful insights, identify trends, and make informed decisions, resulting in improved business outcomes and innovation across industries.

The evolution of analytics reflects this transformation and can be segmented into four distinct eras, each representing a significant leap in the complexity and capability of data analytics. As illustrated in Table 1.1, Analytics 1.0 (1950s) marked the era of Business Intelligence, where businesses began using traditional relational databases for descriptive analytics, laying the groundwork for data-driven decision-making. Analytics 2.0 (mid-2000s) ushered in the Era of Big Data Analytics, characterized by the rise of open-source software and diagnostic analytics, allowing businesses to process unstructured data and gain deeper insights into past events. Analytics 3.0 (mid-2010s) introduced the Era of Data Economy Analytics, where machine learning technologies enabled predictive and prescriptive analytics, prompting significant investments and organizational transformation to leverage these advanced capabilities. The latest phase, Analytics 4.0 (mid-2018s), represents the Era of Artificial Intelligence (AI), where cognitive technologies and AI-driven analytics allow for operational autonomy and automated decision-making. This era demands extensive data resources, advanced methodologies, and strategic innovation as organizations navigate the complexities of AI integration (Davenport, 2019).

This analytics era describes the adoption of AI techniques, achieving operational autonomy, and integrating automated machine learning (ML), which necessitates extensive data resources, advanced statistical methodologies, and distinct investments, skills, and strategic approaches when compared to previous analytics phases.

Table 1.1
Era of Analytics

Analytics 1.0	**Analytic 2.0**	**Analytic 3.0**	**Analytics 4.0**
1950's Era of "Business Intelligence"	Mid 2000s Era of "Big Data Analytics"	Mid 2013's Era of "Data Economy Analytics"	Mid 2018's Era of "Artificial Intelligence"
Traditional relational databases	Open-Source Software	Machine Learning	Cognitive Technologies
Descriptive Analytics	Diagnostic Analytics	Predictive and Prescriptive Analytics	Cognitive Analytics

Source: Adapted from Davenport (2019)

In relation to this, Big Data challenges have become a major concern for organizations, as the massive volume of data demands powerful computational capabilities, statistics, and domain knowledge to uncover trends and patterns (George et al., 2014a; Amalina et al., 2019; Burgener & Rydning, 2022; Shahad Alghamdi et al., 2023). Many organizations find themselves overwhelmed, struggling to make sense of this massive growth in data to drive performance. Although Big Data is widely regarded as a major enabler for many cutting-edge technologies, including AI and ML, its successful implementation is critical to uncovering significant insights and discoveries.

Big Data is an essential component of AI development, providing the massive and diverse information required to train and refine AI algorithms (Alvarez-Napagao et al., 2021; McKinsey Digital, 2023). The relationship between Big Data and AI is mutually reinforcing: Big Data adoption supports AI by providing the necessary data, while AI capabilities increase the demand for more robust data infrastructure and analytics tools. This synergy promotes revolutionary transformations across industries, allowing organizations to get actionable insights and competitive advantages in the data-driven era (Brynjolfsson et al., 2017; McKinsey Digital, 2023).

AI is becoming more and more popular due to its enormous potential uses, increased media and public interest, and unprecedented investment funding. According to Davenport (2019), AI is the extension of data analytics capabilities. Furthermore, the goals of AI and business analytics are very similar: They both use massive data sets, cutting-edge tools and technology, and sophisticated statistical techniques to find new sources of value. For most organizations, AI is positioned as natural evolution expansion of analytics, and thereby benefiting the capabilities of AI to increase work productivity.

Similarly, the adoption of machine learning (ML) has accelerated due to the increase of interest and investment, opening the opportunity of its application through a wider range of tools and services. Because of this expansion and new incoming demands, there is a new spectrum of challenges that many organizations must face. Figure 1.1 illustrate the connectivity between Big Data, AI and ML (Davenport, 2019; Liao et al., 2023; Marr, 2018).

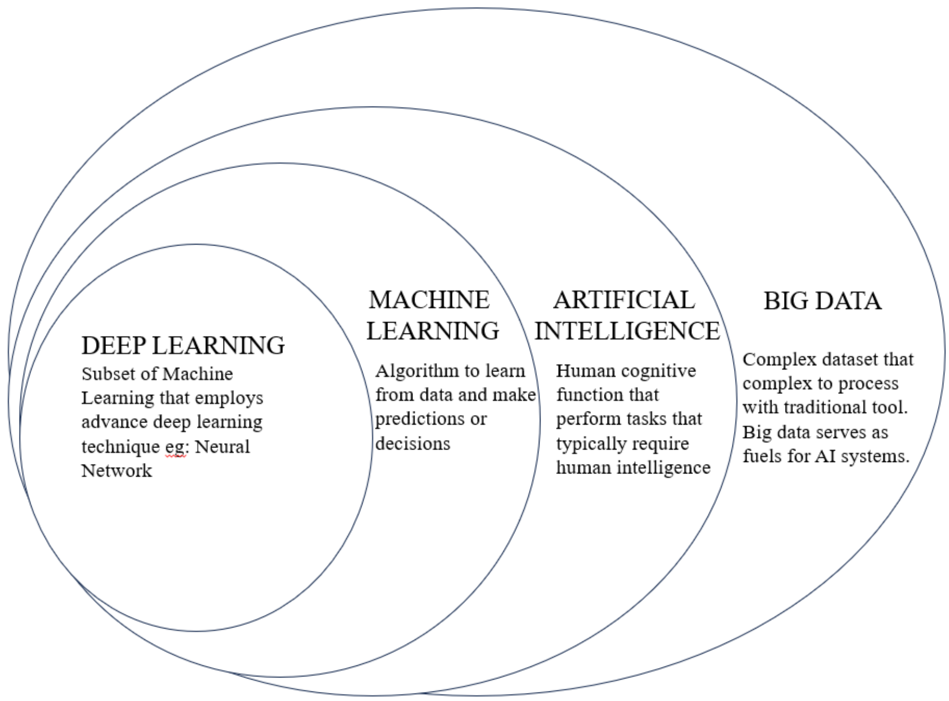

Figure 1.1
Connectivity between Big Data, Artificial Intelligence and Machine Learning
Source: Adapted from Davenport (2019)

As Côrte-Real et al. (2020) stated, forward-thinking companies are on the path to create more holistic approaches to Big Data and analytics that involve the entire organization from end to end. The new insights for Big Data techniques drive the innovation penetration including every aspect of society, which are health care, customer service industry, retail, manufacturing, and financial services (Jagadish et al., 2014). Big data will be an important factor to society and business in the near future. It was believed that Big data adoption will be the latest phenomenon in the predictable future (Gupta & Chaudhari, 2015; Ajah & Nweke, 2019; Muhammad et Aal., 2021; Huynh et al., 2023; Shahad Alghamdi et al., 2023). This shift marks a significant change from traditional business practices, where decisions were often based on intuition or experience. Now, companies must increasingly analyze the data they have available. Big Data is expected to play a crucial role in both business and society in the near future. Experts believe that Big Data adoption will become a defining trend in the foreseeable future. It is anticipated that enormous amounts of information such as Big Data would play a part as the vital need in companies, but the width and understanding of the dissemination do not meet the expectations.

Beyond industrial applications, the combination of Big Data and AI is altering digital landscapes, especially in virtual worlds. Big Data algorithms provide insights into user behavior and preferences, allowing for the production of more immersive experiences. The metaverse's growth also provides fertile ground for generating massive datasets, which pushes future advancements in Big Data and AI (Abu-Salih, 2022; Dwivedi et al., 2022; Sun et al., 2022; Albahri & AlAmoodi, 2023; Asif & Hassan, 2023; Ritterbusch & Teichmann, 2023).

The integration of Big Data and other developing technologies increases their collective advantage. Organizations that use Big Data technology benefit from increased operational efficiency, supply chain management, and innovation via predictive analytics and real-time insights (McKinsey Digital, 2023; Grover et al., 2018; Marr, 2018). Furthermore, Big Data enables personalized marketing strategies, increasing customer engagement and loyalty, whereas AI enables automated decision-making and advanced analytics, promoting business agility in changing market conditions (Mcafee et al., 2023; Vassakis et al., 2018; Davenport, 2019; Sun et al., 2022) .

In today's competitive context, organizations use Big Data-driven decision-making to boost productivity and profitability, with some seeing productivity gains of 8-10% over competitors (McKinsey Digital, 2023). According to Gartner (2023), organizations that effectively incorporate Big Data technologies see 5-6% increases in profitability and increased decision-making capabilities, demonstrating the strategic importance of Big Data.

However, in addition to its benefits, Big Data presents a number of challenges. The vagueness around its description makes it difficult to build a comprehensive framework that spans academics and industry (Ekbia et al., 2015; Favaretto et al., 2020; Id et al., 2020; Liu, 2021). Big Data study is more challenging since it is transdisciplinary, with each field bringing its own ideas and terminologies. Meng (2019) contends that data science, while frequently connected with statistics or machine learning, involves a combination of methodologies that challenge the creation of a single definition. This lack of clarity leads to uncertainty regarding the abilities and tasks required of data professionals, affecting both academic courses and industry standards.

Collaboration between academics and industry to standardize Big Data concepts is critical for exploiting its full potential. Establishing a common understanding would help to facilitate skill development, improve implementation tactics, and encourage the creation of strong data infrastructure. Without this clarity, the growth of both research and practical applications in Big Data will be limited, impeding the realization of its full potential.

A deeper understanding of Big Data is essential for future research and applications. Collaboration between academics and industry to create and standardize Big Data concepts is critical for realizing its full potential and advancing knowledge in this dynamic field. This highlights the necessity for deeper studies in the Big Data space to establish a that could enhance the growth of the body of knowledge and foster collaborations. The lack of a clear definition impedes the advancement of both research and practical applications in data science and Big Data. A collaborative approach to defining and comprehending these terms is crucial to realizing their full potential of Big Data.

1.2.2 Big Data and Organizational Performance – Global Perspective

The usage of Big Data has become the basis of growth and competition for organizations, and has become a critical process for leading companies to outpace their competitions. Companies that harness Big Data effectively are better positioned to improve operational efficiency, market value, and maintain competitive advantages. Big Data helps organizations make better-informed decisions by processing large amounts of structured and unstructured data, resulting in significant performance improvements in these key areas (McGuire et al., 2012; Bhardwaj, 2015; Ghaleb et al., 2023; G. Smith, 2023; Vachkova et al., 2023; Nudurupati et al., 2024). Big Data drives fundamental changes across all industries. Losing market position in a competitive and fast paced market has created a sense of urgency in incorporating Big Data technology into today's organizational decision-making (Thomas & Cook, 2006; Davenport & Dyché, 2013; Favaretto et al., 2020; Lucivero, 2020; Anwar et al., 2021; Muhammad et al., 2021; Wahab et al., 2021).

The rapid proliferation of data in today's digital age has left many organizations feeling overwhelmed and unsure of how to harness its potential effectively. The challenge lies not only in the sheer volume of data but also in the complexity involved in extracting actionable insights that can drive organizational performance (Ejuma Martha Adaga et al., 2024; Taleb et al., 2021). While Big Data is often regarded as cornerstone of modern technological advancements, its implementation with challenges that can impede the discovery of valuable insights (Mikalef & Gupta, 2021) . Many organizations struggle to navigate this landscape, finding themselves perplexed by how to utilize Big Data efficiently to gain a competitive edge (Lunde et al., 2019; Lutfi, Alsyouf, et al., 2022).

The era of digital transformation has dramatically altered the operational landscape for companies, positioning Big Data as an essential tool for achieving organizational success. For example, Netflix and Blockbuster serve as key examples on a global scale, illustrating the critical role of Big Data adoption in their respective successes or failures. This analysis highlights the strategic importance of data utilization in sustaining competitive advantage and emphasizes the dire consequences for companies that fail to invest in digital transformation (Corbet et al., 2021; T. Davis & Higgins, 2013; Es, 2023; Husna et al., 2022; Lechmanová & Vedeikytė, 2020).

One of the most immediate benefits of Big Data is the enhancement of operational efficiency. Big Data allows companies to automate routine tasks, optimize supply chains, and better predict maintenance needs through predictive analytics. Predictive maintenance, driven by Big Data, can reduce equipment downtime by up to 50%, leading to cost savings and increased productivity (McKinsey Digital, 2023). Using

Big Data to streamline logistics can result in a 15% reduction in operational costs, directly impacting the bottom line (Davenport, 2019).

Building on these broader operational benefits, real-world examples illustrate how companies are leveraging Big Data solutions to achieve substantial efficiency gains. The critical insights embedded within Big Data reinforces data-driven decision-making, leading to operational productivity rates and profitability that are 5% to 6% higher than those of competitors (McAfee & Brynjolfsson, 2012). Companies such as GE and Siemens exemplify how organizations can use Big Data to enhance operational efficiency. GE's Industrial Internet platform monitors and analyzes machine performance, enabling real-time decision-making and predictive maintenance. As a result, GE reported a 10% improvement in operational efficiency across its production plants (McKinsey Digital, 2023). Similarly, Siemens' use of Big Data and IoT technologies optimized energy consumption, reducing waste by 15% across its facilities (Siemens, 2021).

Big Data also plays a critical role in increasing market value for organizations. By leveraging Big Data analytics, companies can generate actionable insights that drive innovation and improve product development. BARC (2021) evaluated a variety of businesses and discovered that those adopting big data had an 8% rise in profit and a 10% reduction in cost.

Moreover, Big Data enhances customer engagement through personalization and targeted marketing. For instance, Amazon's use of Big Data for personalized recommendations contributed to a 35% increase in sales (Evdelo, 2020). This real-time analysis of customer preferences enables businesses to create more tailored products and services, impacting customer satisfaction and market value.

Beyond operational efficiency and market value, Big Data provides a substantial competitive advantage. Organizations that can effectively gather, process, and act on data insights outperform their competitors. Companies like Netflix and Amazon have demonstrated how data analytics can drive customer retention, product innovation, and brand loyalty. For example, by utilizing Big Data to predict customer preferences, Netflix reduced churn and increased viewer engagement by 20% within its first year of adoption (Naga Supriya G, 2024). Futhermore, insights from Big Data facilitate accurate pricing strategies, optimize marketing campaigns, and enable effective resource allocation, all crucial for sustaining long-term competitive advantages (Vachkova et al., 2023).

Global perspective: Netflix vs. Blockbuster

Netflix's transformation from a DVD rental service to a global streaming powerhouse exemplifies how big data may be used to achieve extraordinary success. Netflix's early use of big data analytics was critical in identifying user preferences, optimizing content recommendations, and anticipating viewing behaviour (Es, 2023). The corporation used its massive data warehouse to study viewing trends, which guided decisions about content creation and purchase. This data-driven approach not only increased consumer satisfaction but also enabled Netflix to personalize user experiences, which contributed to the company's rapid expansion and domination in the entertainment business.

In contrast, Blockbuster's failure to adapt to the shifting digital market and embrace big data technology is a cautionary story. Blockbuster's demise can be attributed to its slowness to innovate and inability to anticipate the trend toward digital streaming (Al-Ayed et al., 2023; T. Davis & Higgins, 2013). Despite having the option to buy Netflix for a measly $50 million, Blockbuster declined the deal, underestimating the potential of streaming and data-driven services (T. Davis & Higgins, 2013). The company's failure to incorporate big data analytics into its business model made it unprepared to compete with more agile, data-savvy competitors like Netflix, ultimately contributing to its bankruptcy.

According to (Lechmanová & Vedeikytė, 2020) research, Netflix's innovative use of big data transformed the entertainment sector. T. Davis & Higgins, (2013) analyzed how Blockbuster's antiquated business model failed to embrace digital transformation and big data, leading to its bankruptcy. These examples highlight the vital relevance of big data adoption for organizational survival and success in the quickly changing digital age. While Netflix's success and Blockbuster's failure demonstrate the value of Big Data in affecting business outcomes, the advantages extend towards organizational performance financially and non-financially.

In conclusion, Big Data drives operational efficiency, boosts market value, and creates sustainable competitive advantages. Organizations integrating Big Data into decision-making processes are more likely to thrive in today’s dynamic business environment. However, maximizing these benefits requires a robust data strategy, skilled professionals, and a culture that supports data-driven decisions (Nudurupati et al., 2024).

1.2.3 Big Data and Organizational Performance – Malaysia Perspective

Malaysia is increasingly employing Big Data to improve organizational performance, especially in finance, healthcare, and manufacturing. Big Data Analytics has evolved as a crucial tool for companies seeking to increase efficiency, improve decision-making processes, and stimulate innovation (M. T. Huynh et al., 2023). The Malaysian government has recognized Big Data's important role in attaining sustainable development and ensuring the country's competitiveness in the global digital economy (Digital Transformation, 2021) . By incorporating Big Data into their operations, Malaysian businesses can enhance efficiency, cut costs, and innovate in accordance with Industry 4.0 aspirations. The aviation industry, notably the experiences of AirAsia and Malaysia Airlines, provides a clear example of the importance of Big Data in Malaysia.

Malaysian perspective: AirAsia vs. Malaysia Airlines

AirAsia, a pioneer in low-cost flight, has successfully integrated big data into its operations to preserve a competitive advantage. The airline uses big data for a variety of purposes, including route optimization, pricing tactics, and customer relationship management. By researching data on customer preferences and market trends, AirAsia has been able to provide personalized services and competitive pricing, which have been critical to its success in the highly competitive airline sector (Husna et al., 2022). AirAsia's investment in digital platforms and data analytics has resulted in improved operational efficiency, cost reduction, and customer happiness.

Furthermore, Malaysia Airlines' problems were exacerbated by its inability to adequately utilize big data for crisis management, operational efficiency, and consumer engagement (X. Liu et al., 2021). The airline's slow response to digital transformation put it behind competitors that were quicker to integrate big data into their strategic operations. The airline's limited success can be attributed to a failure to capitalize on big data prospects in the early stages.

According to (Husna et al., 2022), AirAsia's success in the airline business stems from its successful use of big data. According to Corbet et al. (2021), study on Malaysia Airlines emphasizes the significance of timely digital adoption in crisis management and operational efficiency . These findings support the view that big data is more than just a technological tool; it is a strategic asset required for navigating competitive markets.

The contrast between AirAsia and Malaysia Airlines highlights the urgency of timely Big Data adoption, which aligns with Malaysia's overall national policy to support digital transformation. AirAsia's success demonstrates the value of using data as a strategic asset, whereas Malaysia Airlines' troubles highlight the repercussions of delayed digital integration. These examples serve as practical validations for Malaysia's Big Data strategy, which aims to provide companies across industries with the tools and frameworks they need to promote growth, innovation, and competitiveness in the global digital economy.

A central focus of Malaysia’s Big Data strategy is the National Big Data Analytics Framework, which was introduced to help companies use data to drive growth. This framework intends to help companies in a variety of industries utilize Big Data technology to improve organizational performance, operational efficiency, and customer experiences (Economic Planning Unit, 2021). Furthermore, the Malaysia Digital Economy Blueprint outlines clear objectives for increasing Big Data adoption among local companies, with a focus on boosting innovation, data-driven decision-making, and strategic competitiveness (MITI, 2023).

The strategic integration of Big Data Analytics into Malaysia's national agenda has boosted organizational performance while also strengthening the country's position as a regional leader in digital transformation. Malaysia is positioned to achieve considerable gains in productivity and competitiveness across multiple industries with additional technological investment and continuing implementation of the National Big Data Analytics Framework (Azman et al., 2021).

Malaysia's significant focus on digital transformation, as seen by programs such as the Malaysia Digital Economy Blueprint and Industry4WRD, demonstrates the government's commitment to developing a data-driven economy (MyGovernment, 2018). The adoption of Big Data technology is consistent with the country's overall aims of raising productivity, improving innovation, and ensuring the long-term viability of its sectors.

With several digital initiatives embarked by Malaysia government via Digital Blueprint, that shows the high interest of Malaysia to be together with global players to take part in digital transformation. Malaysia's comprehensive approach highlights the country's commitment to leveraging Big Data and other advanced technologies. The success of this transformation requires a strong will to deal with massive loads of data and make sense out of data. One of the key players in Malaysia to materialize the success is through Malaysia Digital Economy Corporation (MDEC).

The Malaysia Digital Economy Corporation (MDEC) was established in 1996 as the Multimedia Creation Corporation to oversee the development and implementation of the Multimedia Super Corridor (MSC), a strategic initiative aimed at accelerating Malaysia's transition to a knowledge-based economy (Reid, 1998). MDEC has grown over time to become Malaysia's leading agency for driving digital transformation and technology adoption in all industries. The Malaysian government, through MDEC, is responsible in granting the Malaysia Digital Status to eligible companies that wish to engage in and carry out any of Malaysia's digital operations (MITI, 2023). Companies with Malaysia Digital Status were chosen as data points for this study because they are directly involved in the Malaysia Big Data Initiatives managed by the MDEC (Malaysia Digital Economy Corporation, 2022).

The importance of Malaysia Digital Status companies in the country's Big Data initiatives is reinforced by the substantial incentives provided to these companies under the Malaysia Digital Status program (Global et al., 2024), formerly known as the MSC. With greater flexibility and agility in the offerings, Malaysia Digital Status companies can operate, grow, expand, or invest anywhere in Malaysia. Given the diverse range of incentives and accessibilities available to companies with Malaysia Digital Status, it is particularly pertinent to study Big Data adoption and its impact on organizational performance within these companies. This focus allows for a comprehensive understanding of how these incentives influence the utilization of Big Data and contribute to organizational success. By focusing on Malaysia Digital Status companies, it becomes possible to understand how these incentives help in utilizing Big Data to drive success.

To summarize, Malaysia's strategic integration of Big Data Analytics into its national agenda has greatly enhanced organizational performance and established the country as a regional leader in digital transformation. Malaysia is well-positioned to generate significant gains in productivity and competitiveness across numerous sectors with sustained technological investment and execution of the National Big Data Analytics Framework (Azman et al., 2021).

1.2.4 Big Data and Organizational Performance - Malaysia Digital Status Companies

Malaysia's digital economy has been a substantial contributor to national economic growth, with Malaysia Digital Status companies playing an important role in this change. Malaysia Digital Status (MD) companies, formerly known as MSC Status companies, have received special recognition from the Malaysian government via the Malaysia Digital Economy Corporation (MDEC) for their focus on the digital economy. These companies are well-positioned to leverage emerging technologies such as Big Data, Artificial Intelligence (AI), and the Internet of Things (IoT) to improve operational efficiency and competitiveness (MDEC, 2022c).

The Malaysian government's Digital Economy Blueprint lays out a strategy for promoting the usage of digital technology, and Malaysia Digital Status companies play an important role in accomplishing these objectives. Malaysia Digital Status companies benefit from particular advantages such as tax breaks, subsidies, access to digital expertise, and infrastructure assistance, allowing them to spearhead digital adoption in contrast to traditional organizations, which may lack the same resources (MDEC, 2022; MITI, 2023).

Malaysia's digital economy has been a significant driver of national economic growth. The Malaysia Digital Status under the administration of MDEC has accelerated the adoption of emerging technologies such as Big Data, Artificial Intelligence (AI), and the Internet of Things (IoT), which has contributed significantly to the digital economy's rapid growth. Malaysia's digital economy has made a substantial contribution to its Growth Domestic Product (GDP) and expanded fast, primarily to greater adoption of digital technology and government programs to promote digital transformation. According to Malaysia's Department of Statistics, the digital economy generated 22.6% of the country's GDP in 2020, a considerable increase over prior years (Department of Statistics Malaysia, 2020). The Malaysian government's Digital Economy Blueprint seeks to boost this contribution to 25.5% by 2025, emphasizing the strategic relevance of digital transformation in the country's economic growth.

Table 1.2 summarizes the GDP and Digital Economy Contributions percentage according to year. As Big Data continues to involve into various sectors, its contribution to the digital economy and overall GDP is expected to grow, further enhancing Malaysia's economic landscape.

Table 1.2
Gross Domestic Product (GDP) and Digital Economy Contribution

Year	GDP (USD Billion)	Digital Economy Contribution (%)
2017	320	18.50%
2018	354.5	19.10%
2019	364.7	20.30%
2020	337.7	22.60%
2025 (Target)	N/A	25.50%

Source: Adapted from Department of Statistics Malaysia (2020).

Malaysia Digital Status companies are important stakeholders in this shift. Malaysia Digital Status is a recognition granted to companies that are actively involved in Malaysia's digital transformation efforts, previously known as Multimedia Super Corridor (MSC) Status. These companies benefit from government incentives, including tax exemptions, grants, and access to talent development programs. Managed by the Malaysia Digital Economy Corporation (MDEC), Malaysia Digital Status aims to foster innovation, attract foreign investments, and encourage digital technology adoption, especially in key sectors like finance, telecommunications, and global business services (MDEC, 2022c).

The government incentivizes Malaysia Digital Status companies to use digital technologies that increase operational efficiency, consumer engagement, and decision-making processes. Big Data, in particular, is critical in assisting these businesses in leveraging massive datasets to generate actionable insights, optimize operations, and develop novel services. Malaysia Digital Status companies directly contribute to Malaysia's global competitiveness and GDP growth by utilizing Big Data and related technologies.

Malaysia Digital Status companies are divided into several main clusters ; Global business services, Info Tech, Creative Content & Technologies (Malaysia Digital Economy Corporation, 2022) . Each of the cluster type serves a different aspect of the digital economy. One of the most visible clusters is the Global Business Services (GBS) industry, which has emerged as a crucial driver in Malaysia's digital transformation initiatives. GBS organizations provide shared services on a global scale, such as finance, human resources, and IT, with the goal of boosting operational efficiency, lowering costs, and increasing productivity (PwC, 2021). GBS businesses also play an important part in Malaysia's digitalization efforts by utilizing technologies such as Big Data, Artificial Intelligence (AI), and Robotic Process Automation (RPA) to streamline business processes and increase agility. GBS companies play a large role in the Malaysian economy, accounting for 50% of investments and 66% of exports although being just 20% of the overall number of companies (Malaysia Digital Economy Corporation, 2022). The early adoption of modern technologies, together with Malaysia's supportive ecosystem for digital growth, make the GBS cluster an important subject for research into the influence of Big Data on organizational performance.

GBS companies with Malaysia Digital Status are at the forefront of adopting cutting-edge technologies such as Big Data analytics to streamline their operations, enhance customer service, and improve overall efficiency. For instance, Big Data enables GBS companies to optimize supply chain management, automate routine tasks, and provide personalized services by analyzing massive data sets. This sector is heavily supported by government initiatives, making it a core part of Malaysia's ambition to become a digital hub in Southeast Asia (Digital Transformation, 2021).

Nevertheless, the past studies highlighted several challenges within Malaysian Digital Status companies. Those challenges may impede the full adoption and utilization of Big Data analytics to enhance organizational performance. Technology-Organization-Environment (TOE) framework was employed to identify and construct the determinants of limitations that hinder the efficient utilization of big data solutions. The TOE model, which includes dimensions such as technological complexity, organizational readiness, and environmental factors, is instrumental in analyzing the critical challenges that need to be addressed for organizations to effectively leverage big data solutions. (Hashim et al., 2022; Maroufkhani, Tseng, et al., 2020).

Additionally, inconsistent data quality management practices result in unreliable datasets, making it difficult for companies to extract actionable insights (Taleb et al., 2021). Furthermore, the ease of use of Big Data tools remains a challenge, as many employees face a steep learning curve in effectively utilizing these technologies without adequate training (Hashim et al., 2022). Even with top management support and government incentives provided through Malaysia Digital Status (MDS), there is often a lack of strategic alignment between Big Data initiatives and organizational goals, resulting in slow digital transformation and limited performance improvements (Zian et al., 2024a ; Jayashree et al., 2022; McKinsey Digital, 2023). At the same time, lack of data experts with advanced analytical skills hinders the extraction of valuable insights from data, limiting the effective use of big data within organizations. This highlights the critical role of training as a key factor in enhancing big data adoption, enabling organizations to better meet market demands and remain competitive (Baharuden et al., 2019a; Salleh & Janczewski, 2019; Wahab et al., 2021).

These challenges highlight the need for comprehensive data quality management, robust data security frameworks, user-friendly technologies, effective training programs, and a clear commitment from top management to fully capitalize on the potential of Big Data within Malaysia’s GBS sector.

The strategic importance of the Global Business Services (GBS) sector, together with the government's Malaysia Digital Status program, is key to boosting Malaysia's digital economy. These companies are not only improving their operational capabilities by implementing Big Data solutions but they are also playing an important role in accomplishing national economic objectives.

In contrast, conventional companies frequently suffer resource limits, restricted access to incentives, and delayed adoption of new technology, such as Big Data. These companies often use old operational models, lack real-time data analytics infrastructure, and may fail to prioritize digital transformation due to a lack of strategic alignment (PwC, 2021). Malaysia Digital Status companies, on the other hand, are frequently mandated or encouraged to embrace and integrate sophisticated technologies, such as Big Data solutions, in order to comply with MDEC's digital transformation plans (Malaysia Digital Economy Corporation, 2022). This allows Digital Status companies to prioritize Big Data adoption more readily than conventional companies. Conventional companies, by comparison, may not have the financial backing or digital infrastructure necessary for the large-scale implementation of Big Data technologies. For instance, while Digital Status companies are often mandated or incentivized by MDEC to integrate emerging technologies as part of their compliance with national digital transformation initiatives, conventional companies tend to adopt technologies like Big Data only when absolutely necessary and may lack the strategic alignment to do so efficiently (PwC, 2021; McKinsey Digital, 2023). Furthermore, conventional organizations tend to operate on traditional models that do not easily accommodate the real-time analytics and complex data integration required for effective Big Data utilization, unlike Digital Status companies, which are equipped with the infrastructure to process large datasets and leverage predictive analytics to drive competitiveness (MITI, 2023). Table 1.3 illustrates the differences between Malaysia Digital Status Companies and Conventional Companies.

Table 1.3
Comparison of MD Status Companies vs Non MD Status Companies

Criteria	**MD Status Companies**	**Non MD Status Companies**
Adoption of Digital Technologies	To be eligible for Malaysia Digital (MD) status, companies must focus on approved activities such as Big Data, AI, and IoT, aimed at enhancing operational efficiency and customer engagement (PWC, 2022)	Not included as mandatory criteria to adopt digital technologies, often relying on traditional methods (A. A. Aziz et al., 2023).
Government Incentives	Benefit from tax exemptions, grants, and fast-track immigration for skilled digital talent (MDEC, 2022c)	Limited access to such government-backed incentives and support programs (MITI, 2023).
Talent Development	Access to MDEC-led upskilling programs and a larger pool of digital professionals (Randstad, 2022).	Lesser emphasis on structured upskilling and fewer government-backed programs (A. A. Aziz et al., 2023).

1.2.5 Big Data and Sustainable Development Growth (SDG)

Big data is also crucial for discovering new insights on a global scale, and its great benefits were acknowledged and highlighted into the agenda of the United Nations'

Sustainable Development Goals (SDGs), which were announced in 2015 (Big Data for Sustainable Development, 2015). The United Nations' recognition of Big Data's benefits underlines its significance in increasing knowledge and implementation of sustainable development programs. According to a United Nations report (2015), Big Data is frequently discussed for its applications in pattern recognition, predictive modelling, data monitoring, and neural networks, all of which can help uncover causal relationships and achieve the SDGs.

Integrating Big Data Analytics into the SDGs framework represents a big step forward in tracking and evaluating the progress of sustainable development programs. The 2015 United Nations SDGs offered a comprehensive blueprint that included 17 objectives and 169 criteria for eradicating poverty, protecting the environment, and ensuring prosperity for all. The importance of sustainable development derives from interconnected environmental, social, and economic concerns such as climate change, biodiversity loss, poverty, inequality, and social injustice. These complex concerns require a comprehensive and integrated development strategy that prioritizes equity, resilience, and long-term viability (Big Data for Sustainable Development, 2015; United Nation, 2016; El-Haddadeh et al., 2021). To achieve these ambitious goals by 2030, governments, corporations, civil society, and academia must work together, emphasizing the need of multidisciplinary collaboration and new solutions (Big Data for Sustainable Development, 2015).

With this, the use of Big Data in sustainable development has provided new opportunities for understanding and tackling global concerns. Countries can use sophisticated analytics to make informed decisions that drive economic growth, safeguard the environment, and promote social fairness, all of which contribute to the accomplishment of the SDGs. And this is to emphasize that the benefits of Big Data are not limited to a small-scale approach, but can be applied globally, including the SDG agenda.

The digital adoption, and for this study the Big Data adoption has reshaped industries globally, enhancing organizational performance and fostering a new digital economy. The integration of emerging technologies in Industry 4.0 has imposed advanced data analytics methods to derive meaningful insights and drive decision-making. In Malaysia, while progress has been made in Big Data Analytics maturity, significant challenges remain. Addressing these challenges is crucial for unlocking the full potential of Big Data and driving future innovations. The relationship between Big Data adoption and organizational performance emphasizes the importance of continuous adaptation and improvement to remain competitive in an increasingly digital world.

1.3 Problem Statement

The rapid advancement of technology, driven by digitalization and Industry 4.0, has fundamentally reshaped the global business landscape. In Malaysia, this transition has presented both opportunities and challenges, particularly in managing the exponential growth of data, commonly referred to as "Big Data." Organizations are increasingly focused on leveraging Big Data to drive business value and enhance performance, yet many organizations struggle with the complexity and strategy.

While effective use of Big Data can revolutionize management practices and provide significant competitive advantages, resulting in productivity gains and profitability improvements of up to 5-6% (Bean, Randy; Davenport, 2019; McAfee & Brynjolfsson, 2012); many organizations remain unprepared to become fully data-driven. Factors contributing to this challenge include a lack of strategic vision, limited data analytics capabilities, and the overwhelming process of handling massive amounts of data (Kiron, 2013; Wang et al., 2018; Muhammad et al., 2021; Nilashi et al., 2023).

The onset of the COVID-19 pandemic further amplified the importance of digitalization, as oorganizations faced increased pressure to speed the use of digital and data-driven technology. In today's digital economy, developments in data analytics techniques are crucial for businesses of all kinds to thrive and remain competitive. While this shift has opened new opportunities for companies of all sizes to thrive in the digital economy, it has also introduced complex challenges, particularly in building the necessary data-driven infrastructure and skills (McKinsey, 2018; Tohanean et al., 2018; Mateev, 2020; Wang et al., 2022; Younis, 2022; Global et al., 2024).

In Malaysia, efforts by the government and private sectors, led by organizations like MDEC and MAMPU, have promoted Big Data adoption, yet the adoption rate remains low. According to the National Business Digital Adoption Index report (2022), 64% of companies have not integrated emerging technologies, and 61% express reservations about adopting them.

A significant barrier to Big Data adoption in Malaysia is the shortage of skilled data professionals. Studies highlight that a lack of expertise slows the adoption process and impacts the quality of data-driven projects (Sumathi et al., 2019; Ismail, 2021; Johnson et al., 2021; Falahat et al., 2023; Hafizal Ishak et al., 2023; Ujang et al., 2023). Despite initiatives to develop a skilled workforce of 20,000 data professionals, demand continues to outpace supply, leading to a skills bottleneck that hampers data-driven innovation and limits the effective use of Big Data in Malaysia (Oi, 2022; K. Singh, 2018). Additionally, forecasts indicate that Malaysia will face a shortage of 7,000-15,000 data analysis professionals, exacerbating this difficulty (Yusoff et al., 2021).

According to the report (Randstad, 2022), Malaysia remains a candidate-short market, and this skills gap creates a mismatch between companies' digital growth objectives and the available talent pool. Moreover, 89% of employers recognize a critical need for training to keep pace with rapidly changing skill requirements. This shortage of skilled talent severely impacts Malaysia's capacity to leverage Big Data effectively, which in turn affects the country's broader digital transformation goals.

A thematic analysis of existing literature identifies several critical barriers to Big Data adoption. This process allows for a systematic categorization of qualitative and quantitative data, revealing recurring themes that impede Big Data adoption in organizations (Clarke & Braun, 2014; Naeem et al., 2023). Studies demonstrate that perceived benefits and technological innovations are closely tied to adoption rates (Lai et al., 2018; Pillai & Sivathanu, 2020), with the TOE framework (Technology, Organization, Environment) providing a valuable structure to understand the role of these elements in adoption decisions (Tornatzky & Fletscher, 1990; Arunachalam & Kumar, 2018; Al-Rahmi et al., 2019; Loh & Teoh, 2021; Sekli & De La Vega, 2021; Vachkova et al., 2023; Asiri et al., 2024).

In addition to TOE, the Resource-Based View (RBV) Theory (Barney, 1991) contributes to this study by emphasizing training as a moderating element. RBV contends that intangible resources such as human skills and organizational knowledge are critical to maintaining a competitive advantage. Training can greatly improve organizational performance by providing people with the skills they need to use Big Data technology (Asiri et al., 2024).

Building on the TOE framework's three key components; technology, organization, and environment. The technology element includes data quality and ease of use because these are essential technological factors that represent core technology attribute that have a direct impact on the effectiveness and usefulness of Big Data systems. High-quality data ensures accurate analysis, while ease of use influences user accessibility and technology acceptance (Parulian et al., 2023; Shanmugam et al., 2023). Data quality was chosen as the primary technological focus since it is essential for the accuracy and reliability of Big Data analytics. Without reliable data, even advanced technologies yield poor decision-making outcomes
(Shanmugam et al., 2023).

The organizational element, particularly top management support, is essential for fostering innovation adoption, as it directly influences resource allocation, strategic alignment, and employee motivation. Without strong managerial support, businesses may lack the strategy alignment and commitment necessary for successful technological integration (Tabesh et al., 2019).

Finally, data security is classified as an environmental element since it involves fulfilling external regulatory requirements, complying with data protection laws, and handling external dangers such as cyber threats. Data security was chosen as a critical factor because it is required to maintain the confidentiality, integrity, and availability of information in Big Data systems. As more data is acquired through digital media and online platforms, the risk of security breaches and cyber threats grows considerably. This has made data security an essential component in assuring the preservation of sensitive information. Without adequate security measures, companies suffer financial loss, regulatory noncompliance, and reputational damage (Anawar et al., 2022).

By examining these factors through the comprehensive lens of the TOE framework, which integrates both internal and external factors, it becomes clear that each component not only influences Big Data adoption individually but also interacts dynamically with broader environmental conditions and industry standards. These factors have been identified as the most significant determinants of successful Big Data adoption in several empirical studies (Nilashi et al., 2023; Solana-González et al., 2021; Arunachalam & Kumar, 2018; Shanmugam et al., 2023;Al-madhrahi et al., 2022; Taleb et al., 2021; Salleh & Janczewski, 2019; Thanabalan et al., 2024;Kim & Cho, 2018; Mangla et al., 2020a)(Asiri et al., 2024; Marr, 2018 ; Ajah & Nweke, 2019; Smith, 2023; Abdullah Sani et al., 2021; Amalina et al., 2019; Al-madhrahi et al., 2022; Dias et al., 2021; Hafizal Ishak et al., 2023; Hamzah et al., 2020; Reyes-Veras et al., 2021; Shahbaz et al., 2019; Wook et al., 2021).

The TOE framework's distinction of these factors contributes to a comprehensive understanding of technology adoption in businesses, as evidenced by various empirical studies that link these factors to organizational success (Hashim et al., 2021; Tornatzky & Fletscher, 1990). In summary, the TOE framework offers a holistic perspective on the multidimensional lens of technology adoption. TOE is one of the highly used framework to study about innovation adoption as researchers can get significant insights into the elements that drive or impede innovation adoption by investigating the interaction of technology capabilities, organizational readiness, and environmental forces (Bryan & Zuva, 2021). Due to the above result, there is a need to study the adoption of Big Data within the context of technology, organization, environment and training effectiveness for proper implementation and better return of investment to the organizational performance.

Data quality management presents significant technological challenges and is often prioritized because accurate insights are essential for data-driven decision-making; low-quality data can lead to incorrect conclusions, making it one of the most important technological considerations (Ghasemaghaei & Calic, 2019; X.-L. Meng, 2023). In Malaysia's Big Data landscape, studies have highlighted recurring issues with data accuracy, completeness, consistency, timeliness, and reliability (Ijab et al., 2019; Wook et al., 2021; Dias et al., 2021). Furthermore, challenges such as inadequate data governance and the lack of standard rules for data quality management practices have been cited as barriers (Chuah & Thurusamry, 2021; Hamzah et al., 2020; Ibrahim Ahmed et al., 2023; Vachkova et al., 2023; Zian et al., 2024b).

However, some evidence contradicts the evidence that data quality has a direct impact on organizational effectiveness. Ghasemaghaei and Calic (2019), and Ali (2023) conducted studies that indicated no significant association between data quality and organizational performance. These studies argue that other elements, like leadership, strategic alignment, and staff competence, are more important in predicting organizational outcomes. Furthermore, Ali (2023) revealed that, while data quality is frequently regarded as critical, its direct impact on performance indicators was shown to be minor. This reveals a possible gap in the empirical understanding of how data quality effects performance, underlining the need for more study to explore these dynamics in other organizational situations. According to Zhanga; et al. (2022; Eng and Lin (2012) and Al-hiyari et al. (2013), the unexpected finding of non-significant relation of data quality, partly because of previous researchers may have seen that high-quality data can be manipulated by management, to obscure scorecard on earning management. For example, managers attempt to change company metrics to make themselves seem better or meet performance goals that are linked to their bonuses or stock awards. This manipulation worsens the inconsistency of research findings, emphasizing the need for additional research to fully understand the relationship between data quality management and organizational effectiveness. As a result of these inconsistent findings, there is a compelling need to re-examine and investigate the relationship between data quality management and organizational performance.

Data security emerges as the recent and significant barrier as Malaysia progresses in its endeavors to enhance its Big Data strategies. Despite efforts by public and private sectors to promote Big Data analysis, concerns about data security persist, affecting user adoption and organizational preparedness. It was also reported around 60% did not have enough knowledge on managing threats in their organizations (Hamzah et al., 2020). Data security presents significant environmental challenges as it involves in dealing with data exposure of personal information or known as data privacy, compliance practice and regulatory orchestrations. Data security was chosen as a critical factor because confidentiality, integrity, and availability of information in Big Data systems. loss, regulatory noncompliance, and reputational damage (Anawar et al., 2022). (Hamzah et al., 2020; Harun et al., 2022; Anawar et al., 2022). Furthermore, limited access to necessary data remains pivotal concern as noted by Hamzah et al. (2020).

Although data security is widely seen as an important issue in the adoption of Big Data technologies, evidence reveals that concerns about data security do not significantly impede the adoption process. For example, the relationship is less significant, particularly in environments where organizations prioritize operational efficiency over stringent security measures (T. N. Huynh et al., 2023 ; Yadegaridehkordi et al., 2018; Haddad et al., 2019; Ghasemaghaei, 2020; Mahdi Nasrollahi, Javaneh Ramezani, 2021). Because of this, there is a need for further studies to explore the relationship and measure the influence of data security and organizational performance.

Ease of use presents significant technological challenges that hinder the advancement and effective utilization of Big Data initiatives supported by previous studies (Soon et al., 2016; Al-Rahmi et al., 2019; Baharuden et al., 2019a, 2019b; Hamzah et al., 2020; Harun et al., 2022; Ujang et al., 2023; Zian et al., 2024). Generally, the complexity and perceived difficulty of using Big Data technologies are seen as major barriers to the adoption of Big Data. Zian et al. (2024), Ujang et al. (2023), and Al-Rahmi et al.

(2019) highlighted about the importance of user friendly interfaces. The complexity of Big Data technologies can overwhelm users and deter them from pursuing the utilization of Big Data technologies.

In contrast to these findings, some studies found no substantial link between ease of use and organizational effectiveness. For example, Parulian et al. (2023) argued that, while ease of use is important for initial adoption, it does not always translate into enhanced organizational performance. This can be demonstrated in cases where an organization quickly adopts a new big data tool because of its user-friendly interface, but the technology's ease of use fails to solve deeper organizational concerns such as data integration, aligning the technology with strategic goals, and ensuring that staff are well-trained to use the system (Yunis et al., 2018; Parulian et al., 2023). As a result, the organization may not see significant increases in efficiency, decision-making quality, or profitability. The contradictory findings demonstrate that, while ease of use is important for adoption, its impact on performance may be limited, necessitating a more thorough evaluation of other organizational factors (Yunis et al., 2018; Parulian et al., 2023). With that, there is a need for further studies to explore the relationship and measure the influence of ease of use and organizational performance.

Top Management support is critical to support the organization's direction in adopting any new innovations. As noted by Mohamad et al. (2020), management support plays a significant role in influencing the staff workers and provide the endorsement for organization's strategy. For example, effective training supported by management will increase the workers motivation to learn and subsequently adopt new technologies such as analytics tools. This is also consistent with Hong and Ping (2020) and Hashim et al. (2021), who described top management support as a vital organizational entity that support necessary allocation of resources, manage resistance, and ensure that strategic goals align with technological initiatives. Having strong management support is essential to secure robust adoption strategy and foster the culture of trust and alignment with the organization's goals. Some of the empirical studies highlighted a significant relationship between top management support and organizational performance (Abdullah et al., 2017; Ijab et al., 2019; Hamzah et al., 2020; Hong & Ping, 2020a; Mangla et al., 2020a; Mohamad et al., 2020; Abdullah Sani et al., 2021; Ghaleb et al., 2021; Hashim et al., 2021; Muhammad et al., 2021; Harun et al., 2022; Hashim et al., 2022; Lutfi et al., 2022; Ibrahim Ahmed et al., 2023; Aziz et al., 2024; Zian et al., 2024).

Contrary to these findings, some research have revealed no substantial association between top management support and organizational success. Elbanna and Newman (2022) contend that, while senior management support is required to initiate and sustain technological adoption, it does not directly translate into greater organizational performance. Some studies highlighted that factors such as data integration and operational competencies are frequently more important in sustaining long-term effectiveness (T. N. Huynh et al., 2023). Similarly, there have been reports of contradictory findings on the relationship between top management support and technology adoption in various industries (Alsetoohy et al., 2019; Fareed & Su, 2022; Jayeola et al., 2022).

These contradictory findings indicate that, while top management support is important for strategic alignment, its direct impact on organizational performance may be limited, requiring a more comprehensive approach to organizational performance. That shows there is a need for further studies to explore the relationship and measure the influence of top management support and organizational performance.

Finally, training is another critical factor to be evaluated as indicated earlier that talent shortage is one of the major concerns that cause the delay of Big Data adoption rate in Malaysia. Numerous studies have suggested that training acts as a significant role in increasing the adoption rate and removing the stigma of hard-to-use associated to new technologies (Al-Rahmi et al., 2019; Baharuden et al., 2019a, 2019b; Harun et al., 2022; Kamarulzaman & Hassan, 2019a; Lutfi, Al-Khasawneh, et al., 2022). As noted by Harun et al. (2022), training and skill development have a notable impact on user intentions to embrace Big Data technologies within educational institutions in Malaysia, primarily by enhancing perceived ease of use and usefulness. Similarly, Chuah and Thurusamry (2021) emphasized the importance of well-designed training to utilize the analytical tool. For example, there is limited analytical tool that is user friendly, either it's highly complex tool and require highly skilled workforce or simple tool but not useful. Moreover, Al-Rahmi et al. (2019) highlighted the work around knowledge sharing and ongoing professional development through training positively influence the behavioral intention to utilize Big Data, ultimately facilitating smoother adoption processes.

On the contrary, evidence reveals that training does not always result in improved organizational performance and might occasionally have a negative or minimal influence. For example, training can easily become outdated due to lack of continuous support and adaptations of skills (Akter et al., 2016; Mahmood et al., 2023). Moreover, there is limited research on Big Data adoption in Malaysia that evaluates training as moderator and not thoroughly investigated in all dimension of technology, organization and environment (Al-Rahmi et al., 2019; Baharuden et al., 2019b; Chuah & Thurusamry, 2021; Harun et al., 2022; Thanabalan et al., 2024).

In conclusion, while the TOE framework offers a structured approach to analyzing Big Data adoption, inconsistencies in empirical findings indicate that factors such as data quality, data security, ease of use, top management support, and training may not have a consistent impact on organizational performance. The lack of consensus in existing studies emphasizes the necessity for a thorough analysis into these aspects and their interdependence, particularly within Malaysia's organizational structure. This study aims to address these research gaps by analyzing the moderating function of training and providing insights into how these elements combined lead to the effective adoption of Big Data for improved organizational performance.

1.4 Research Questions

The questions listed are based on the subjects discussed in the research problem which are data quality management, data security, ease of use, and top management support in relation to organizational performance. The study will focus on organization companies in Malaysia under Digital Status Companies (previously known as Malaysia Super Corridor–MSC) registered under MDEC as one of major industries that benefit the value creation from Big Data (Hashim et al., 2021; Younis, 2022). These questions will drive data collection and analysis to determine organizational performance.

RQ1 : What is the relationship of data quality management in Big Data adoption and organizational performance.

RQ2 : What is the relationship of data security in Big Data adoption and organizational performance.

RQ3 : What is the relationship of ease of use in Big Data adoption and organizational performance.

RQ4: What is the relationship of top management support in Big Data adoption and organizational performance.

RQ5: What is the moderating effect of training on the relationship of data quality management, data security, ease of use, and top management support in Big Data in increasing organizational performance.

1.5 Research Objectives

The objectives of this research are:

RO1 : To examine the relationship between data quality management in Big Data adoption and organizational performance.

RO2: To examine the relationship of data security in Big Data adoption and organizational performance.

RO3: To examine the relationship of ease of use in Big Data adoption and organizational performance.

RO4: To examine the relationship between top management support in Big Data adoption and organizational performance.

RO5: To examine the moderating effect of training on the relationship of data quality management, data security, ease of use, and top management support in Big Data adoption and its impact in increasing organizational performance.

1.6 Scope of the Study

The focus of this study was to evaluate connection of data quality management, data security, ease of use, and top management support in Big Data adoption and their impacts on organizational performance. The main interest of the study was to examine organizational response in adopting technology related to Big Data. The main scope of this study was limited to Malaysia digital status companies under cluster of Global Business Services registered under MDEC.

Global Business Services (GBS) is an operational business model that consolidates and streamlines numerous business processes and services across several locations, often on a global scale. The GBS model usually combines the multiple services such as finance, human resources, information technology etc. Although GBS companies covers 20% of total number of active Malaysia Digital Status companies, the companies contributed the largest to performance of overall Malaysia Digital Status companies in Malaysia (Global et al., 2024). GBS companies were chosen due to their direct involvement with MDEC initiatives and having accessibility to incentives and support.

1.7 Significance of the Study

This study critically examines the relationship between data quality management, data security, ease of use, and top management support in Big Data adoption and their impacts on organizational performance. The role of training is essential in increasing Big Data adoption by equipping organizations with a more skilled workforce, enabling them to effectively manage and integrate Big Data technologies. The current situation, where uncertainties and challenges prevail, reveals a scarcity of empirical investigations among Malaysian companies (Chuah & Thurusamry, 2021; Hashim et al., 2021; Loh & Teoh, 2021; Wahab et al., 2021; Hashim et al., 2022; Ibrahim Ahmed et al., 2023; Ujang et al., 2023; Zian et al., 2024). This scarcity emphasizes the need for further exploration and systematic re-evaluation of methodologies, as indicated by Id et al. (2020).

This study investigates the relationship between these determinants and organizational performance in Malaysia Digital Status companies in the Global Business Services (GBS) sector. Results of the study will provide a complete understanding of how these determinants influence organizational performance. This information is critical for enhancing operational efficiency and competitiveness. The findings will benefit practitioners and academicians, contributing to Malaysia's productivity and enriching the body of knowledge in the field of data-driven performance.

Additionally, this research holds significant importance in addressing crucial gaps in the adoption of Big Data among companies in Malaysia. It supports the initiatives outlined in the Digital Blueprint Malaysia (Digital Transformation, 2021; Lo, 2021)., providing valuable insights by identifying gaps and offering theoritical and practical contributions.

1.7.1 Theoretical Contributions

This study contributes to the existing body of knowledge by examining the impact of data quality management, data security, ease of use, and top management support on organizational performance across Malaysia Digital Status organizations in the Global Business Services (GBS) sector. It expands the current theoretical framework by including training as a moderating component, providing a new lens through which Big Data adoption can be understood in terms of organizational performance.

Existing studies commonly use the Technology-Organization-Environment (TOE) framework or the Resource-Based View (RBV) theory to analyze innovation and technology adoption (Zhu et al., 2003). However, there is limited studies that combines both theories to provide a broader overview of Big Data adoption, particularly among Malaysian Digital Status organizations. The merger of TOE (which focuses on external factors) with RBV (which emphasizes internal resources such as training) is still underexplored. This study seeks to close this gap by developing a complete model that integrates the TOE and RBV frameworks to examine how both external and internal factors influence Big Data adoption and its impact on organizational performance.

1.7.2 Practical Contributions

This study provides several practical contributions to Malaysia Digital Status companies in the Global Business Services (GBS) sector. By examining the relationship between data quality management, data security, ease of use, and top management support in Big Data adoption, the findings offer actionable insights for business leaders and policymakers to improve organizational performance. It helps GBS organizations optimize their Big Data strategies to enhance operational efficiency and competitiveness.

Most Big Data studies in Malaysia focus on SMEs or public sector organizations (Atan, 2022; Chuah & Thurusamry, 2021), leaving a significant gap in understanding the unique challenges faced by Malaysia Digital Status companies, particularly in the GBS sector. This study addresses this practical gap by focusing specifically on

Malaysia Digital Status companies to uncover how they leverage Big Data technologies to enhance organizational performance and global competitiveness (N. A. Aziz et al., 2024).

Moreover, given the rapid pace of technological progress, training is also critical for ensuring the staff workers can properly use new Big Data technologies. In particular, the role of training as a critical moderator influencing adoption outcomes has been underexplored, particularly in the Malaysian context companies (Baharuden et al., 2019b; Ibrahim Ahmed et al., 2023). Although both internal capabilities and external technological factors are often considered in studies using frameworks like TOE and RBV, the impact of targeted training on enhancing Big Data adoption and improving performance remains insufficiently examined. This study seeks to address this gap by investigating how training, as an internal resource, strengthens or weakens the effects of TOE factors on organizational performance in Malaysia Digital Status.

This alignment goes beyond technology and includes organizational strategy, where training may assist bridge the skills gap, support data-driven decision-making, and improve staff efficiency. Previous studies have discussed about training as future studies, companies that invest in training programs are more likely to overcome hurdles connected with ease of use, data security concerns, and top management support, resulting in higher organizational performance outcomes (Baharuden et al., 2019b; Chong et al., 2023; Harun et al., 2022; Lutfi, Al-Khasawneh, et al., 2022).

Furthermore, it contributes to the existing literature on the GBS sector in Malaysia by providing empirical insights into how these companies leverage Big Data to optimize operational efficiency and competitiveness. This study explores an under explored area by focusing on training as a moderating factor, emphasizing the importance of workforce readiness in successful Big Data adoption and organizational performance enhancement.

1.8 Definition of Key Terms

This section summarizes some of the important terms used and will aid in understanding the concept of this study. Table 1.4 displays definition for each variable in this research.

Table 1.4
Definition of Key Terms

Variables	Conceptual Definition	Source
Organizational Performance	Organizational performance is defined as the measurement of how well a business achieves its goals and objectives, taking into account both financial and non-financial metrics. It entails assessing different variables such as efficiency, effectiveness, productivity, and quality, and it reflects an organization's total success in meeting its strategic objectives. Technology advancements and advanced analytics are essential for improving these metrics, aligning operations with strategic goals, and ensuring long-term success.	(Thanabalan et al., 2024; Sinclair & Zairi, 1996)
Training	Training is a structured process to enhance employees' skills and competencies, aligning them with the organization's strategic goals. Effective training is crucial for enabling staff to use Big Data tools, adapt to business needs, and drive innovation and competitive advantage.	(Chong et al., 2023 Baharuden et al., 2019a)
Data Quality Management	Data quality refers to the extent to which data meets the accuracy, completeness, consistency, and relevance criteria required for effective decision-making. High-quality data guarantees that information utilized in decision-making processes is trustworthy, timely, and aligned with organizational goals, therefore increasing the overall efficiency and effectiveness of decision-making in information-intensive contexts.	(Khong et al., 2023)
Data Security	Data security refers to a comprehensive collection of practices, technologies, and policies designed to safeguard digital data from unauthorized access, breaches, and other malicious activity in the digital environment. This includes guaranteeing data confidentiality, integrity, and availability throughout its lifecycle, especially in the context of Big Data, where the amount, diversity, and velocity of data complicate the maintenance of safe data environments.	(Egho-Promise & Sitti, 2024)

Variables	Conceptual Definition	Source
Ease of Use	Ease of use refers to how easily users can interact with a system to achieve specific goals effectively and efficiently, impacting their willingness to adopt new technologies. In Big Data Solutions, ease of use enhances user satisfaction and system performance by reducing the mental effort required, promoting smoother adoption through intuitive design and low complexity.	(J. Wang et al., 2024)
Top Management Support	Top management support involves senior executives actively participating and endorsing Big Data Adoption strategy, ensuring alignment of resources and goals with technological advancements. This support is crucial for overcoming resistance to change, fostering innovation, and ensuring the successful and sustainable adoption of new technologies within the organization.	(Lutfi, Al-Khasawneh, et al., 2022; Maroufkhani, Wan Ismail, et al., 2020)

1.9 Organization of the Thesis

This section aims to provide overall view on the organization of the thesis, ensuring an understanding of how the research is systematically presented and how each chapter contributes to addressing the research questions and objectives.

Thesis Outline

This thesis consists of five (5) chapters, as described below, and Figure 1.2 illustrates the framework of the thesis.

Chapter 1 presents a general outlook of Big Data on the global overview and Malaysia perspective. This chapter begins with introduction, research background, research problem, research questions, research objectives, research scope, limitations and significance of the research.

Chapter 2 outlines comprehensive review of literature highlights on key factors of technology, organization and environment, and the role of internal resources such as training in influencing big data adoption towards organizational performance. This chapter delves into critical determinants that influence Big Data Adoption. The determinants are examined through the underpinning theories; Technology-Organization-Environment (TOE) framework, and the Resource-Based View (RBV) to explore training as a moderating factor. The chapter concludes by synthesizing the research gaps and proposing hypotheses to address how Big Data adoption can drive organizational success, particularly within Malaysia Digital Status companies.

In the contributors toward Big Data adoption influences organizational performance. This chapter includes literature review on Big Data adoption, implementation of Big Data adoption in Malaysia, the overview of technical and non-technical aspects, and the underpinning theories to support the research objectives.

Chapter 3 describes the theoretical of research methodology framework for the study, which explicitly explains the comparison of research method analysis. It begins with hypothesis and development framework. This chapter specifies the type of unit of analysis and an explanation of the questionnaire's design. Finally, the chapter entails analyzing the measurement model, conducting validity and reliability tests, and most importantly the type of predictive result of the analysis.

Chapter 4 explains the overall result of data collection through statistical analysis. It begins with the description of demographic distribution, followed by data screening and preliminary analysis. Subsequently, the chapter proceeds to evaluate the measurement model by conducting validity and reliability tests. The evaluation of the inner model, which looks at the links inside the study framework through hypothesis testing, R-squared values and effect sizes. This chapter examines the theoretical framework by conducting the testing for conceptual framework and describes the result in statistical manner.

Chapter 5 summarizes the main conclusions and research goals. This chapter outlines the research findings, summarizes the relationships, and contribution in the perspective of academia and industry. It also highlights the significance and non-significance of results with several recommendations for future studies.

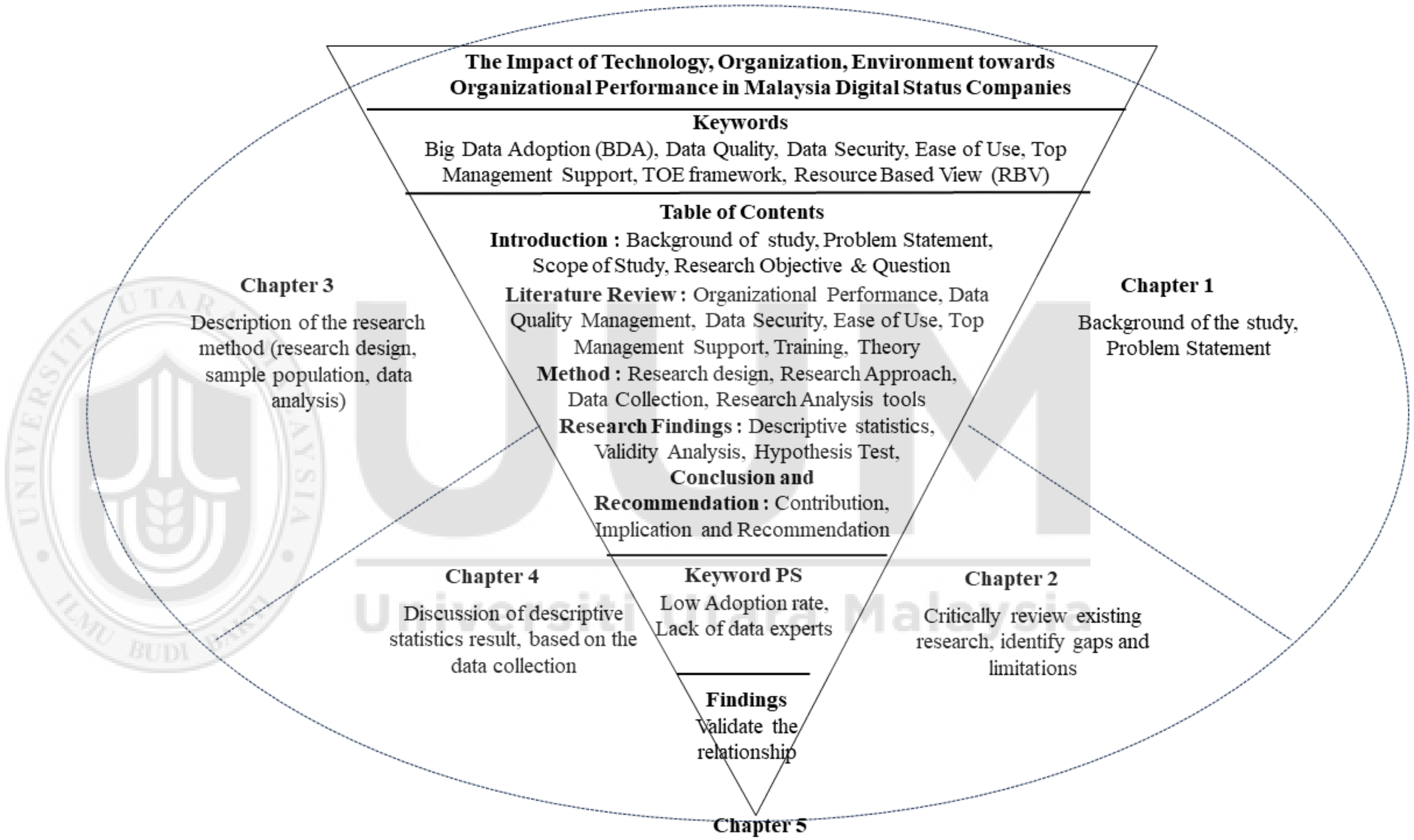

Figure 1.2
Thesis Framework
Source: Adopted from Zainan Nazri (2024)

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides an overview of the literature on big data adoption, as well as the factors that influence an organization's technology adoption. This study primarily searched for and synthesized ideas and background concepts concerning technology adoption, technology factors, organizational variables, environmental factors, and internal resources. This chapter addresses key practical and theoretical issues highlighted in Chapter 1, focusing on the slow adoption of Big Data in Malaysia and the unresolved challenges affecting organizational performance. From a practical standpoint, the study explores specific determinants such as the data quality management, data security , ease of use, as well top management support within Malaysia Digital Status companies (MDEC, 2022a). These determinants hinder effective implementation, leading to poor organizational outcomes. Theoretical gaps are also evident, with inconsistent findings on the impact of determinants on organizational performance (Ghasemaghaei & Calic, 2019; Ghasemaghaei & Calic, 2019). Moreover, the role of training as a moderator remains underexplored, despite being a critical factor for effective adoption (Hashim et al., 2021; M. T. Huynh et al., 2023). This study aims to bridge these gaps by integrating the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV) theory to develop a holistic model that explains the interaction between key drivers and organizational performance in the context of Big Data adoption.

2.2 Overview of Big Data

Big Data has transformed how organizations collect, process, and utilize data, necessitating the development of new technologies to manage the vast datasets generated. The sheer volume of data available has overwhelmed traditional systems and approaches, leading to the development of new technologies and methodologies to capture, store, manage, and analyze this data (Amin et al., 2018; Marr, 2018).

The incorporation of Big Data into organizational strategy has been extensively researched, demonstrating its impact on boosting organizational performance and competitive advantage (Vassakis et al., 2018; Baharuden et al., 2019a; Maroufkhani et al., 2019; Hong & Ping, 2020b; Wahab et al., 2020; Loh & Teoh, 2021; Lutfi et al., 2022; Mohd et al., 2022; Ghaleb et al., 2023; Asiri et al., 2024; Aziz et al., 2024; Nudurupati et al., 2024; Thanabalan et al., 2024; Zian et al., 2024).

2.2.1 Big Data Definition

The term “Big Data” refers to the significant rise of datasets in terms of size, diversity, and complexity, making them difficult to process using standard methods and demanding the development of new ways for extracting insights. According to Oxford English Dictionary (2013), Big Data is described “sets of information (datasets) that are too large or too complex to handle, difficult to analyze using standard methods”.

Various experts have defined Big Data differently over the years. Table 2.1 illustrates the list of Big Data Definitions to give an overall summary of the definition.

Table 2.1
List of Big Data Definition

Author	Year	Definition
Simplilearn	2024	The term "Big Data" refers to a big volume of data. In other terms, Big Data refers to data that has higher variety, volume, and velocity. Thus, they are also known as the three Vs. These enormous and complicated data can be structured, semi-structured, or unstructured, and they cannot be analyzed using typical data processing methods (Simplilearn, 2024).
Investopedia	2024	Big data refers to vast, diversified sets of information that are growing at an exponential rate. The term refers to the volume of information, the speed at which it is generated and collected, and the diversity or scope of the data points covered (Investopedia, 2024).
International Data Corporation (IDC)	2019	Data intelligence uses business, technological, relational, and operational metadata to provide openness about data profiles, classification, quality, location, lineage, and context. Empowering people, processes, and technology with reliable and trustworthy data (IDC, 2019).
Forbes	2013	Big Data is a collection of data from traditional and digital sources inside and outside your company that represents a source for ongoing discovery and analysis (Forbes, 2013).
Oxford Dictionary English	2013	Data of a very large size, typically to the extent that its manipulation and management present significant logistical challenges (Oxford English Dictionary, 2013).
Gartner	2013	Big Data is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation (Gartner Inc., 2013).
O'Reilly Media	2012	Data that exceeds the processing capacity of conventional database systems. The data is too big, moves too fast, or doesn't fit the strictures of your database architectures (O'Reilly Media, 2012).
McKinsey	2011	Datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze (McKinsey & Company, 2011).
Doug Laney (Gartner)	2001	Big Data is volume, variety, and velocity—as the key data quality management challenges (Laney, 2001).

2.2.2 Big Data Evolution

The evolution of Big Data can be traced back to the 1960s, when early Database Management Systems (DBMS) such as IBM's IMS revolutionized data processing and played a critical part in important initiatives like NASA's Apollo program (Aron, 1969; Targowski, 2016) . During this time, businesses began to invest in technology that laid the groundwork for modern data analytics (Bhardwaj & Johari, 2015; Ajah & Nweke, 2019; Nasrollahi et al., 2021). The emergence of relational databases, pioneered by Edgar F. Codd in the 1970s, was a big step forward in data accessibility and consistency (Khan et al., 2014; Ajah & Nweke, 2019).

Business Intelligence (BI) tools arose in the 1980s, enabling companies to make strategic use of data. OLAP (Online Analytical Processing) also made it easier to analyze massive datasets, hence improving data management skills (Golfarelli et al., 2004; Tavera Romero et al., 2021; Sun et al., 2018; Zohuri, 2020; Tavera Romero et al., 2021; Sun et al., 2022; Bharadiya & Bharadiya, 2023; Praful, 2023). The term "Big Data" first appeared in the 1990s, and BI technologies expanded in response to the advent of the internet and digital storage (Cox & Ellsworth, 1997). The introduction of NoSQL databases in the 2000s signalled the start of the Big Data era, as data complexity and volume increased (Connolly & Wooledge, 2012).

By the 2010s, Big Data Analytics had become critical to organizational performance, allowing companies to acquire a competitive advantage through data-driven decision-making (Brynjolfsson et al., 2011; Cai & Zhu, 2015; Davenport et al., 2010). The 2020s saw the introduction of disruptive technologies such as AI, blockchain, and the Metaverse, which enabled real-time data analysis while improving data privacy and cooperation (Abu-Salih, 2022; Dwivedi et al., 2022; Sun et al., 2022). Figure 2.1 illustrates the overall view of Big Data Historical timeline.

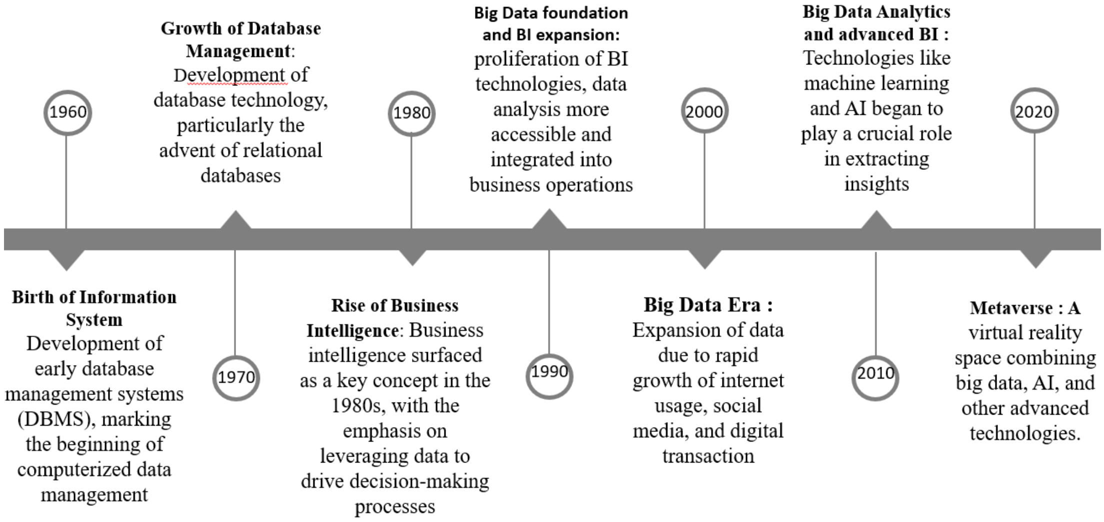

Figure 2.1
Big Data Historical Timeline

2.2.3 Big Data Characteristics

The evolution of Big Data is a fascinating journey that combines technological improvements and exponential data growth. Understanding this history demands exploration into the numerous phases and advancements that have paved the way from early data collection to the present era of immersive technologies and predictive analytics. Figure 2.2 illustrates the Vs of Big Data and Table 2.2 provides the description of the Vs.

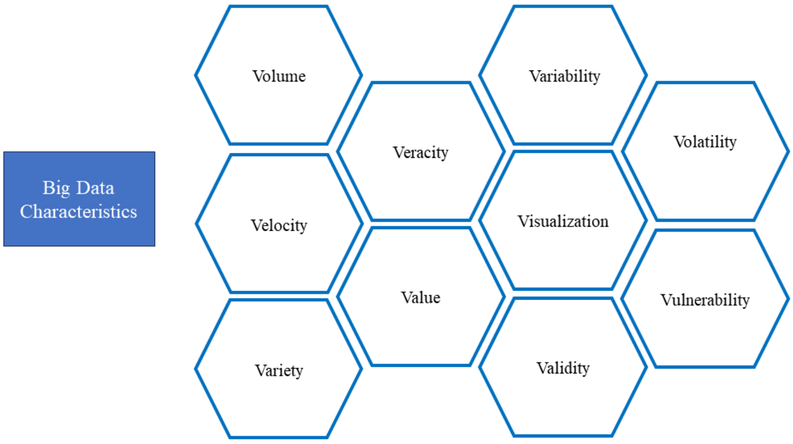

Figure 2.2
Big Data Characteristics—10Vs

Table 2.2
Description of Big Data Characteristics

No.	Characteristic	Description	Reference
1	Volume	Refers to the scalability size of data generated every second.	(Laney, 2001)
2	Velocity	The speed of the data generated.	(Laney, 2001)
3	Variety	The various types of data (structured, unstructured, semi-structured).	(Laney, 2001)
4	Veracity	The state of quality and trustworthiness of the data.	(IBM, 2013)
5	Value	The benefits and valuable insights derived from the data.	(IBM, 2013)
6	Variability	The variations in data sources and formats.	Huysegoms et al., 2013
7	Visualization	The pictogram view or visual format of the data to capture attention and bring into decisions.	Huysegoms et al., 2013
8	Validity	Examining the authorized data source and accuracy of the data for the right intended use.	(Ranjan, 2019)
9	Volatility	The movement of data and latency it remains relevant and accessible.	(Ranjan, 2019)
10	Vulnerability	Related to security and sensibility of data, to ensure data is protected	(Ranjan, 2019)

2.2.4 Big Data Benefits and Challenges

Big data has transformed various aspects of modern business and society. Research consistently shows that integrating Big Data with business intelligence improves decision-making, enhances operational efficiency, and drives innovation (Bean, Randy; Davenport, 2019; Davenport, 2019; Ejuma Martha Adaga et al., 2024; Nabbosa & Kaar, 2020).

The relationship between Data, Information, Knowledge, and Wisdom is visually represented in Figure 2.3, showing how raw data can be transformed into actionable insights through the DIKW model, while Figure 2.4 illustrates the Big Data Analytics Maturity Model, which highlights the progression from descriptive to prescriptive analytics, demonstrating how organizations that adopt advanced analytics techniques achieve optimized decision-making and maintain a competitive edge.

DIKW Pyramid

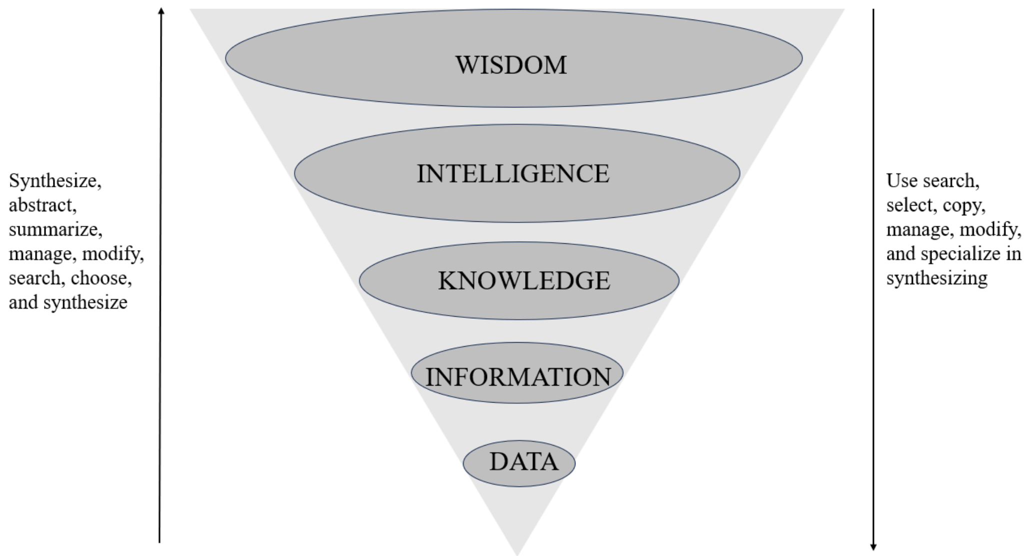

Figure 2.3
The Relationship Between Data, Information, Knowledge, Experience, and Wisdom (DIKW Pyramid)

Source: Adapted from Sun and Huo (2020)

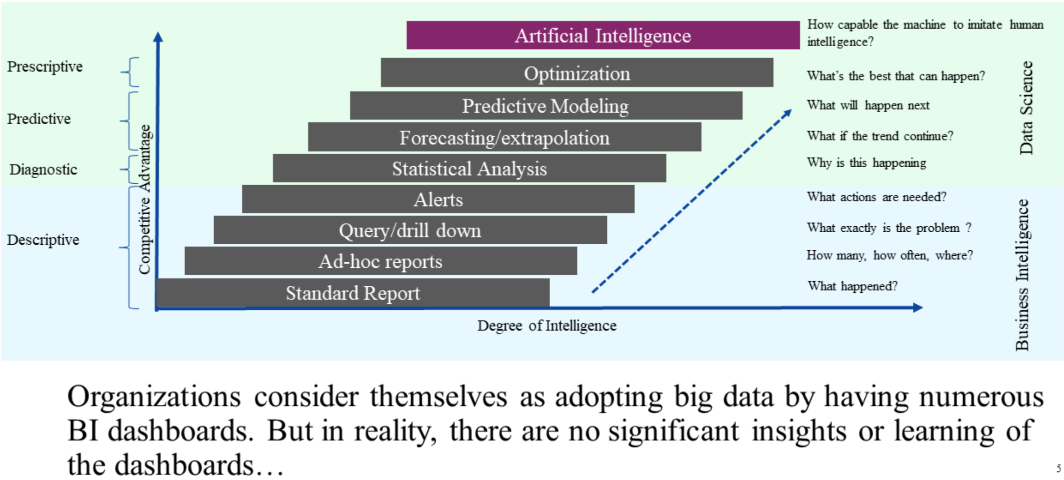

Figure 2.4
Big Data Analytics Maturity Model
Source : Adapted from (Davenport, 2019)

Big Data Challenges

Big data adoption in organizations has a number of issues that have an impact on organizational performance, particularly in terms of data quality management (Al-madhrahi et al., 2022; Arunachalam & Kumar, 2018; Nilashi et al., 2023; Shanmugam et al., 2023; Solana-González et al., 2021; Taleb et al., 2021), data security (Asiri et al., 2024; Kim & Cho, 2018; Mangla et al., 2020a; Marr, 2018; Salleh & Janczewski, 2019; Thanabalan et al., 2024), ease of use (Abdullah Sani et al., 2021; Ajah & Nweke, 2019; Al-madhrahi et al., 2022; Amalina et al., 2019; Dias et al., 2021; Smith, 2023), and support from top management (Hafizal Ishak et al., 2023; Hamzah et al., 2020; Reyes-Veras et al., 2021; Shahbaz et al., 2019; Wook et al., 2021).

Data quality problems in Big Data landscape have been documented in various studies, including issues such as data accuracy, completeness, consistency, timeliness, and reliability (Fatt & Ramadas, 2018; Nilashi et al., 2023; Solana-González et al., 2021 ; Arunachalam & Kumar, 2018; Onyeabor & Ta'a, 2018; Shanmugam et al., 2023). Poor data quality impedes effective decision-making and operational efficiency, negatively affects organizational performance by hindering effective decision-making and operational efficiency (Onyeabor & Ta'a, 2018; Ghasemaghaei & Calic, 2019; Taleb et al., 2021; Ali, 2023a; Khong et al., 2023; Nilashi et al., 2023; Shanmugam et al., 2023). Additionally, the absence of effective data quality management frameworks exacerbates these challenges, leading to poor decision-making and reduced trust in data-driven insights (Ijab et al., 2019; Khong et al., 2023).

Data security issues are another significant impediment. Data breaches and cyber-attacks are common concerns for organizations, posing considerable dangers to the security and confidentiality of their data (Anawar et al., 2022; Thanabalan et al., 2024). Ensuring data privacy and protecting against cyber-attacks are critical to sustaining confidence and reliability in Big Data systems. Data security problems, such as the danger of breaches, security threats, and concern on data privacy, impede the use of Big Data technology (Kim & Cho, 2018; Kamarulzaman & Hassan, 2019a; Dias, 2021; Dias et al., 2021; Liu, 2021; Falahat et al., 2023). Failure to appropriately safeguard data can result in regulatory problems, stifling economic growth, inefficient operations, and a loss of business value.

Ease of use is another critical component in the adoption of technology. The complexity of Big Data tools, as well as the obstacles associated with their integration, contribute to poor adoption rates. Many Big Data solutions are not simple and require significant effort to integrate with existing systems. This complexity can hinder businesses from implementing new technologies, resulting in resistance to change and a lack of innovative values (Zian et al., 2024b). Simplifying and making these technologies more user–friendly is critical for increasing uptake and utilization, which can enhance operational efficiency and time to market. While ease of use is critical for initial adoption, issues such as tool complexity, lack of intuitiveness, and difficulty integrating with legacy systems can arise. However, ease of use does not always translate into enhanced organizational performance, highlighting the importance of ongoing training and support (Ajah & Nweke, 2019; Baig et al., 2019; Bornet & Wirtz, 2021; Ismail, 2021; Lutfi, Al-Khasawneh, et al., 2022).

The backing of top management is essential for the successful implementation of Big Data solutions. A lack of awareness and comprehension, combined with shifting priorities, can limit the adoption of these technologies (Hashim et al., 2022; Kamarulzaman & Hassan, 2019a). Top management must be dedicated to creating a data-driven culture and providing the resources and support required for Big Data efforts. Without this support, organizations may face a competitive disadvantage and miss out on the business benefits that Big Data may deliver. Furthermore, top management support is vital, as dedication and awareness of big data’s strategic significance are required for successful adoption and long-term performance benefits (Lee et al., 2018; Mangla et al., 2020a; Mangla et al., 2020b; Maroufkhani, Tseng, et al., 2020; Elbanna & Newman, 2022; Fareed & Su, 2022; Jayeola et al., 2022; Lutfi, Al-Khasawneh, et al., 2022). These problems highlight the necessity for a comprehensive approach to big data adoption that addresses technical, organizational, and environmental variables in order to improve overall organizational performance.

To summarize, tackling the difficulties of data quality management, data security, ease of use, and top management support is critical for increasing the adoption of Big Data solutions.

2.3 Organizational Performance

Organizational performance refers to how well an organization meets its goals and objectives. Measuring this performance entails comparing actual outputs to projected outcomes, with an emphasis on important measures such as income and expenses, sales, and shareholder earnings (Neely, 2002; Gavrea et al., 2011). Recent research emphasizes the use of sophisticated analytics and data-driven decision-making to improve these metrics (Davenport, 2019). Income and expenses demonstrate financial health, sales show market performance, and shareholder earnings evaluate investment returns. Robust data rules and analysis techniques are critical for accurate assessment, informed decision-making, and ongoing development (Côrte-Real et al., 2020; Dias et al., 2021). By concentrating on these essential performance metrics, companies can align their operations with their strategic vision, increase stakeholder satisfaction, and achieve long-term success (Neely, 2002).

According to Sinclair and Zairi (1996), the fundamental of assessing organizational performance are to:

a) Establish clear and accurate communication.

b) Assist managers in implementing new viewpoints.

c) Individually encourage and promote the development of more appropriate organizational behavior.

d) Provide efficient and effective planning and control structures.

e) Support and enlarge improvement initiatives.

f) Assist organizations to divide their resources in attractive development activities.

g) Support the management's creativity and change management.

The following section provides an overview and landscape of Malaysia Digital Status Companies as the entity of organizational performance for this study.

2.3.1 Definition of Malaysia Digital Status Companies

The establishment of Malaysia Digital Status (MD) organizations, formerly known as Multimedia Super Corridor (MSC), has been critical in accelerating Malaysia's transition to a digital economy and encouraging the adoption of new technology. The Multimedia Super Corridor (MSC) was launched in 1996, a plan to drive the country into the information and knowledge era. This national program, rebranded as Malaysia Digital in 2022 (MITI, 2023), is led by the Malaysia Digital Economy Corporation (MDEC) and aims to position Malaysia as a global leader in the digital economy.

The main objective of Malaysia Digital Status is to promote the growth of Malaysia's digital economy and strengthen its position as a global digital hub. This goal is in line with the broader vision outlined in the Malaysia Digital Economy Blueprint (Digital Transformation, 2021). This goal is in line with the broader vision outlined in the Malaysia Digital Economy Blueprint (MyDIGITAL), which aims to position Malaysia as a leader in the regional digital economy by 2030 (Economic Planning Unit, 2021).

The initiative aims to improve the digital ecosystem by attracting foreign direct investment (FDI) and local companies in technological areas, creating high-value jobs, and promoting technology transfer.

To be eligible for Malaysia Digital Status, companies must meet specific requirements:

a) **Company Incorporation**: The company must be incorporated under the Companies Act 2016 and must be a resident in Malaysia (MDEC, 2024).
b) **Engagement in Malaysia Digital Activities**: The company must propose to carry out or be currently engaged in one or more Malaysia Digital activities, which include software development, data analytics, cybersecurity, and creative content generation (MDEC, 2024; MITI, 2023).

Malaysia Digital Status companies are benefiting with various of incentives:

a) **Tax Incentives**:
    i. Income tax exemptions on statutory income for up to ten years.
    ii. 100% Investment Tax Allowance on qualifying capital expenditure (MDEC, 2024).
b) **Grants and Infrastructure Support**:
    i. Access to world-class infrastructure and financial grants aimed at improving operational efficiency and supporting innovation (MDEC, 2024).
c) **Legislative and Intellectual Property Support**:
    i. Facilitation of intellectual property rights protection, which is crucial for software development and creative content companies (MDEC, 2024).

d) **Immigration Process Facilitation**:

i. Streamlined immigration processes to attract and retain global talent, supporting sectors like IT and software development that rely on highly skilled professionals (Economic Planning Unit, 2021; MDEC, 2022a).

The Malaysia Digital status categorizes companies into main clusters; Global Business Services (GBS), Information Technology (InfoTech), and Digital Creative Content (DCC) (Malaysia Digital Economy Corporation, 2022).

The Global Business Services (GBS) Cluster

The GBS cluster specializes in centralized and integrated service delivery methods, such as shared services, business process outsourcing, and knowledge-based services (Malaysia Digital Economy Corporation, 2022). It has been the most significant contributor to Malaysia Digital's investments, accounting for more than half of all investments and 74% of export value by H1 2022 (Malaysia Digital Economy Corporation, 2022). This achievement demonstrates GBS's critical role in increasing Malaysia's competitiveness in the global digital economy, which is fuelled by investor-friendly regulations and the availability of skilled talent.

Information Technology (InfoTech) Cluster

The InfoTech cluster includes companies that specialize in software development, systems integration, AI, IoT, and data analytics. It expanded at an 18.2% CAGR between 2017 and 2021, demonstrating high investor confidence and demand for digital solutions (Malaysia Digital Economy Corporation, 2022).

Digital Creative Content (DCC) Cluster

The DCC cluster consists of companies that create and enhance digital content, such as broadcasting, game creation, and animation to promote global digital economy (Malaysia Digital Economy Corporation, 2022).

As these companies continue to integrate digital technology, the role of Big Data becomes increasingly important. MDEC facilitates this transition by providing incentives to encourage the adoption of digital technologies, which enhances MD status companies' capacities in resource management, risk assessment, and strategic decision-making (Malaysia Digital Economy Corporation, 2022). The successful integration of Big Data technology within these companies frequently leads to considerable improvements in operational performance, highlighting the symbiotic relationship between Big Data adoption and Malaysia's digital economic advancement (SRS, 2023).

2.3.2 Big Data Evolution in Malaysia

Big Data Evolution—Historical Timeline

Big Data initiatives in Malaysia began in 2014 with the National Big Data Adoption (BDA) program, which aimed to establish Malaysia as a regional hub for Big Data Analytics (MDEC, 2014). The initiative promoted collaboration between the public and private sectors, laying the groundwork for future advancements. In 2015, MDEC released the Big Data Framework, which outlined a five-year strategic plan that included the development of a national steering committee and the hiring of a chief data scientist to oversee the strategy's implementation (MDEC, 2015). The 11th

Malaysia Plan (2016-2020) incorporated Big Data into the national agenda, with an emphasis on reforming the public sector and lowering government expenses through data-driven insights (Economic Planning Unit, 2016).

To summarize, the history of Big Data projects in Malaysia demonstrates a strong commitment to becoming a regional hub for Big Data Analytics. MDEC's strategic efforts, as represented in national frameworks and talent development programs, have considerably improved the country's capabilities in this area. Continuous collaboration between the public and private sectors, as well as educational institutions, is critical to continuing this growth. As Malaysia continues to invest and prioritize Big Data, it is positioned to gain significant economic benefits and establish itself as a leader in the digital economy. Figure 2.5 summarizes the overall timeline of Big Data initiatives and the evolution of it.

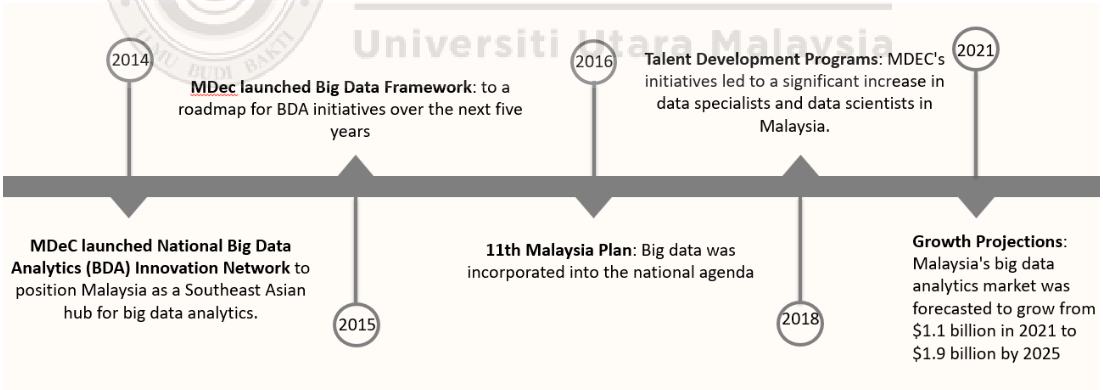

Figure 2.5
Big Data Initiatives in Malaysia—Historical Timeline

2.3.3 Impacts of Big Data to Organizational Performance

Big Data adoption has a substantial impact on organizational performance for organizations with Malaysia Digital status. As these businesses embrace digital transformation, the ability to leverage Big Data becomes a critical driver of success. Big Data offers Malaysia Digital status organizations the tools they need to evaluate and interpret complex datasets, resulting in more effective strategic planning and execution. However, there is still a significant need for further empirical studies, particularly focusing on Malaysia Digital Status companies (see Table 2.3 for a summary of previous research papers in Malaysia pertaining to Big Data Adoption).

Table 2.3
Previous Research Papers for Big Data Adoption in Malaysia

Author(s)	Year	Industry	Title	Key Findings	Research Type
(Zian et al., 2024)	2024	Education	Technological, organizational and environmental factors influencing on user intention towards Big Data technology adoption in Malaysian educational organization	Propose suitable technologies, intensive training programs, and managerial support to encourage data-driven decision-making, and collaborate with legislators on Big Data adoption. Theoretical: Combines the TAM, DOI, and TOE frameworks to improve understanding of Big Data adoption in education.	Conceptual
(Aziz et al., 2024)	2024	Hotel	The impact of Big Data Analytics on innovation capability and sustainability performance of hotels: evidence from an emerging economy	Achieving benefits involves technology infrastructure, data management capabilities, and a data-driven culture, stressing BDA's importance in innovation and competitive advantage.	Conceptual
(Ghaleb et al., 2023)	2023	Healthcare	Assessing the Big Data Adoption Readiness Role in Healthcare between Technology Impact Factors and Intention to Adopt Big Data	Higher technological preparedness correlates with a stronger desire to use Big Data, emphasizing the importance of robust infrastructure and security.	Empirical Analysis
(Vachkova et al., 2023)	2023	SME	Big data and predictive analytics and Malaysian micro-, small and medium businesses	The study underscores the challenges that SMEs face, such as limited funds, qualified labor, and technological infrastructure, but also finds them more adaptive to Big Data adoption. Government incentives and training can help boost their competitiveness and growth.	Empirical Analysis

Table 2.3 (Continued)

Author(s)	Year	Industry	Title	Key Findings	Research Type
(Ibrahim Ahmed et al., 2023)	2023	Manufacturing	Rationalizing Factors Influencing the Effective Utilization of Big Data in Malaysian Fintech Companies	The report emphasizes technical preparedness, a competent workforce, and a strong infrastructure. Fintech requires strategic investments and regulatory assistance to harness Big Data for service, efficiency, and competitiveness.	Conceptual
(Abdullah Sani et al., 2023)	2023	Public	Technology, Organization and Environment as Strategic Factors of Big Data Analytics Readiness and Acquisition Intention to adopt Big Data Analytics in Malaysian Libraries	The study finds that legal, architectural, social, and market factors are significant challenges for SMEs in adopting Big Data Analytics, according to Lessig's Four Modalities.	Empirical Analysis
(Hashim et al., 2022)	2022	Public	A TOE Approach for Big Data Adoption Factors Towards Organizational Impact in the Malaysia's GLAs: A Conceptual Review	The paper reviews factors influencing Big Data adoption in Malaysia's Government-Linked Agencies using the TOE framework, categorizing key factors under technology, organization, and environment. It highlights a structured approach to addressing Big Data adoption challenges in the public sector.	Conceptual
(Anawar et al., 2022)	2022	Telecommunication	Security and Privacy Challenges of Big Data Adoption: A Qualitative Study in Telecommunication Industry	highlights security and privacy issues related to telecom Big Data adoption, emphasizing threats from data breaches, complex regulatory frameworks, and obsolete IT infrastructure.	Empirical Analysis

Table 2.3 (Continued)

Author(s)	Year	Industry	Title	Key Findings	Research Type
(Atan, 2022)	2022	SME	Technology, Organization, Environment, Organization culture, adoption of business analytics in small, medium companies	To use Business Analytics, SMEs should develop a comprehensive plan that considers technology, organization, environment, and culture. This strategy improves decision-making, operational efficiency, and corporate performance. Empirical analysis supports this integrated technique.	Empirical Analysis
(Wahab et al., 2021)	2021	Manufacturing	Big Data Analytics adoption: An empirical study in the Malaysian warehousing sector	The study identifies relative advantage, technological infrastructure, absorptive capabilities, and government backing as critical determinants in BDA adoption, but industry competition has no significant impact.	Conceptual
(Dias, 2021)	2021	Healthcare	The Impact of Big Data Utilization on Malaysian Government Hospital Performance	The study indicates that BDA adoption significantly enhances strategic agility and performance of healthcare in Malaysia.	Empirical Analysis
(Chuah & Thurusamry, 2021)	2021	SME	Challenges of Big Data adoption in Malaysia SMEs based on Lessig's modalities: A systematic review	Relative advantage, technological infrastructure, absorptive aptitude, and government assistance are crucial for BDA acceptance, although industry competition has little influence.	Conceptual

Table 2.3 (Continued)

Author(s)	Year	Industry	Title	Key Findings	Research Type
(Hashim et al., 2021)	2021	MSC	Conceptualizing the relationship between Big Data Adoption (BDA) factors and Organizational Impact (IO)	The study finds that relative advantage, technological infrastructure, absorptive capabilities, and government backing are crucial for BDA adoption in the warehousing sector, while industry competition is minimal.	Conceptual
(Loh & Teoh, 2021)	2021	SME	The Adoption of Big Data Analytics Among Manufacturing Small and Medium Enterprises During Covid-19 Crisis in Malaysia	The impact of Big Data Analytics adoption on the performance of Malaysian small and medium companies	Empirical Analysis
(Hong & Ping, 2020)	2020	SME	The Impact of Big Data Analytics Adoption on the Performance of Malaysian Small and Medium Companies	The impact of Big Data Analytics adoption on the performance of Malaysian small and medium companies	Conceptual

Recent studies on Big Data adoption in Malaysia, particularly in Malaysia Digital Status companies, highlight a rising interest in both conceptual and empirical investigations. From 2016 to 2024, research on Big Data adoption in various industries shows a consistent increase in focus, with empirical studies gaining attention in recent years. For example, 17 out of 26 studies conducted during this period were conceptual, while 9 focused on empirical investigations, with a peak in 2021 (Figure 2.6). While Figure 2.7 provides a visual depiction of Big Data adoption studies in Malaysia by industry from 2016 to 2024, shows that research on Malaysia Digital Status companies are limited. As a matter of fact, the visualization only includes one study in the "MSC" category. This highlights a substantial gap in the literature, indicating the necessity for more empirical studies to investigate the practical and measurable impact of Big Data adoption within Malaysia Digital Status companies. This constraint emphasizes the significance of future research that collects and analyzes empirical data to better understand how Malaysia Digital Status companies might use Big Data to improve organizational performance.

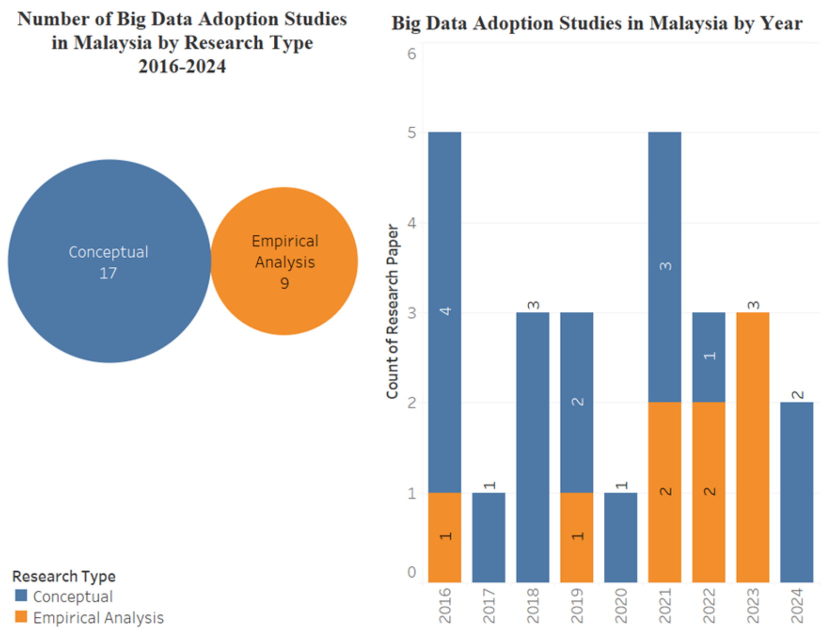

Figure 2.6
Distribution of Previous Studies on Big Data Adoption in Malaysia

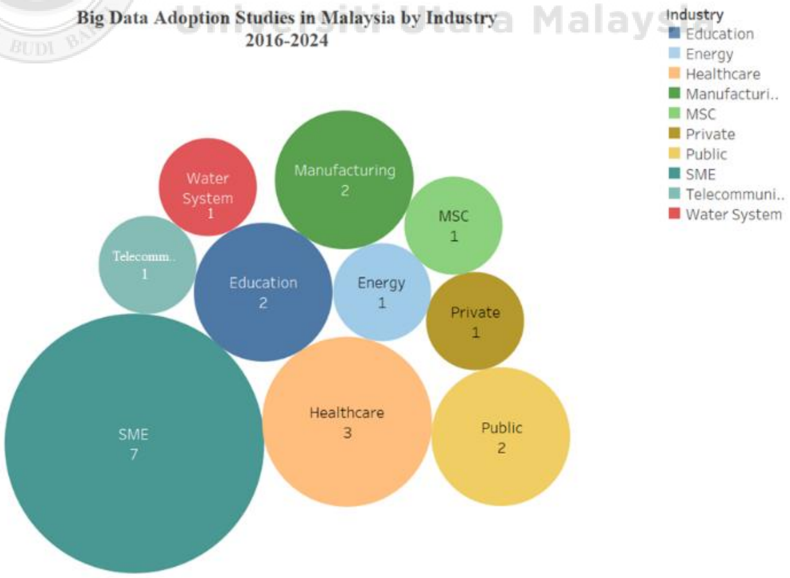

Figure 2.7
Distribution of Previous Studies on Big Data Adoption in Malaysia by Industry

Challenges for Outsourcing Models within Malaysia Digital Status Companies

Despite the benefits impose in Big Data, many organizations, particularly those in outsourcing-driven sectors such as Global Business Services (GBS), struggle to properly integrate Big Data technologies. GBS companies focus on centralizing back-office and IT services like finance, HR, IT support, and BPO (Global et al., 2024; Ojukwu et al., 2015). They play a significant role in outsourcing services, especially for multinational clients looking for operational efficiency. Other Malaysia Digital Status companies, outside the GBS sector, may not have outsourcing as their primary business model (Global et al., 2024).

Outsourcing frequently delivers operational efficiencies and access to cutting-edge technologies, but it also generates dependencies that might limit internal innovation capacities and impede in-house talent development (Akbari, 2024; Hanafizadeh & Zareravasan, 2020; Ojukwu et al., 2015). These organizations, particularly those that specialize in BPO and IT services, are increasingly relying on third-party vendors for Big Data services.

Outsourcing can improve operations, particularly for multinational clients, but it may dilute the strategic focus essential for long-term digital innovation. Malaysia Digital status companies must combine outsourcing benefits with domestic capacity growth to maintain data sovereignty, security, and national norms (Hanafizadeh & Zareravasan, 2020; Varajão et al., 2017; Ojukwu et al., 2015). This reliance poses strategic issues, especially when outsourcing impedes the internal development of Big Data skills (Iranmanesh et al., 2023).

The current literature on outsourcing stresses cost efficiency and scalability (Hanafizadeh & Zareravasan, 2020; Ojukwu et al., 2015; Varajão et al., 2017), but it frequently ignores its impact on strategic innovation, particularly in the context of Big Data implementation. This is especially important considering the strict compliance requirements set by MDEC. While the operational benefits of outsourcing are well documented, the strategic drawbacks, particularly in terms of impeding long-term innovation, have received less attention (Iranmanesh et al., 2023).

The unique model of Malaysia Digital Status companies within Global Business Services (GBS) present both opportunities and challenges to Big Data adoption. Outsourcing provides access to current technologies and skills, but it also dilutes the strategic focus required for long-term digital innovation. Despite these hurdles, organizations that successfully integrate Big Data technology would benefit greatly in terms of operational.

More empirical study is needed to understand how Malaysia Digital Status companies balance business model and internal innovation. The little research on Malaysian Digital Status companies highlights the need for more research into how these organisations meeting the balance of company direction on outsourcing and sustain technology experts and remain competitive. Companies relying on third-party providers face issues in data protection, customization, and compliance with local requirements (Hanafizadeh & Zareravasan, 2020; Ojukwu et al., 2015).

2.4 Data Quality Management

Incomplete and inconsistent data, as well as mistakes, pose substantial challenges to the successful use of Big Data. High-quality data is essential for reliable analysis and decision-making. Data quality can go beyond correctness and includes characteristics such as relevance, completeness, timeliness, and accessibility (Wang, 1996; J. Wang et al., 2024).

Issues with data quality might result in inaccurate insights, affecting the organization's operational decisions and strategic direction (Arunachalam & Kumar, 2018; Taleb et al., 2018, 2021; Ghasemaghaei & Calic, 2019; Wook et al., 2021; Nilashi et al., 2023). A lack of effective data quality management techniques can lead to customer attrition (Marr, 2018; Thanabalan et al., 2024).

Unstructured data is unquestionably growing rapidly. It is more difficult to find and analyze unstructured data than organized data. According to Taleb et al. (2018) & Edge (2024), 80% of the data generated is thought to be unstructured. Indeed, evaluating the quality of unstructured data is a tedious task and laborious. The need for high-quality data is essential if companies are to devote more time to analytics techniques rather than putting in the tedious job of cleaning and extracting the data. Organizations are recognizing the importance of segregating and organizing their data to enhance decision making while upholding business values (Solana-González et al., 2021). The issue of data quality is described in Table 2.4, which illustrates previous studies related to data quality.

Table 2.4
Previous Studies Related to Data Quality

Year	Author	Title	Key Findings
2023	Shanmugam et al.	The Management of Data Quality Assessment in Big Data Presents a Complex Challenge, Accompanied by Various Issues Related to Data Quality	Identified difficult obstacles in maintaining data quality in large data contexts, shedding light on a variety of data quality issues.
2021	Meng	Enhancing (publications on) data quality: Deeper data mining and fuller data confession	Methods for improving data quality were discussed, including deep data mining techniques and complete data confession methodologies.
2019	Meng	Data Science: An Artificial Ecosystem	Examined data science's artificial ecology and its consequences for data quality control.
2018	Wahyudi et al.	A Process Pattern Model for Tackling and Improving Big Data Quality	Proposed a process pattern model for enhancing large data quality, with a focus on systematic responses to quality challenges.
2019	Ijab et al.	Conceptualizing Big Data Quality framework from a systematic literature review perspective	A thorough evaluation of large data quality frameworks was conducted to identify essential dimensions and obstacles in sustaining data quality.
2018	Wahyudi et al.	Improving Big Data Quality	Strategies for increasing the quality of Big Data were highlighted, with an emphasis on organizational and technical methods.
2018	Onyeabor and Ta'a	Big data and data quality dimensions: a survey	Big data quality, identifying obstacles and recommending methods to improve data quality.
2018	Taleb et al.	Big Data Quality Framework: A Holistic Approach to Continuous Quality Management	Developed a holistic framework for ongoing quality management in Big Data, highlighting the importance of complete initiatives.

2.4.1 Data Quality Management and Organizational Performance

Complexity in data quality management portrays chaos of data–as introduced by its characteristics of volume, speed and assortment, which at that point prompts apparent complexity in Big Data adoption. More elevated amount of apparent data chaos will create larger amount of uncertainty and apparently may not bring values to the companies (David A. Hsieh, 2020; Haryadi et al., 2016; Yadegaridehkordi et al.; 2018). Data quality is commonly associated with three primary focus that generally discussed in previous studies which are incomplete, inaccurate and inconsistent (Wook et al., 2021).

Incomplete

With the growth of Big Data, data quality administration has become a crucial area of study. Even little mistakes can result in inaccurate insights, process inefficiencies, revenue losses, and an inability to comply with industry and governmental regulations in the absence of proper data quality management (Ali, 2023). The testing tasks include securing organized huge data that is complex from various sources and successfully integrating it. When there is minimal data, it can be verified manually by making an inquiry and using Extract, Transform, Load (ETL) or Extract, Load, Transform (ELT) (Arunachalam & Kumar, 2018; Al-madhrahi et al., 2022)(Arunachalam & Kumar, 2018). It is hard to gather, clean, coordinate, and lastly get the required excellent data inside a viable time allotment. Since the amount of unstructured data in large datasets will provide an exceptional opportunity to transform unstructured data into organized categories and conduct additional data processing (Ghasemaghaei & Calic, 2019; Mahmood et al., 2020; Dias, 2021). Indeed, data quality management remains a major challenge for the current data processing techniques.

Inaccurate

In the aspect of data inaccuracy, Onyeabor and Ta'a (2018) and Shanmugam et al. (2023) emphasized that incorrect data significantly reduces operational efficiency. Shanmugam et al. (2023) state that mistakes result in inaccurate assessments, which can disrupt supply chains, manufacturing operations, and service delivery. According to Onyeabor & Ta'a (2018) and Mikalef & Gupta (2021), these disruptions can result in increased operational costs and inefficiencies since organizations must invest more resources to remedy errors and mitigate their effects. In the health sector, accuracy in data presents substantial issues for businesses.

Inconsistent

Inconsistent data quality is another significant impediment to organizational success because it disturbs operational efficiency, impedes efficient decision-making and strategic planning, and hampers data integration efforts (Dias, 2021). These difficulties underline the vital necessity for reliable and accurate data to guarantee that organizational operations run smoothly and efficiently.

A research on Big Data issues from an ASEAN perspective underlines how inconsistent data can cause substantial problems in data interpretation and utilization (Alfred, 2019). Alfred (2019) highlighted missing knowledge impairs the ability to create accurate insights, which are required for informed decision-making. Similarly, inconsistent data undermines the reliability of data-driven insights, leading to flawed decision-making and strategic misalignments. Al-madhrahi et al. (2022) emphasized that inconsistent data undermines the reliability of data-driven insights, leading to flawed decision-making and strategic misalignments. This constraint prevents businesses from properly comprehending their operations and market situations, resulting in strategic and operational inefficiencies. Figure 2.8 illustrates the integration of Data Lifecycle Management with the TOE framework, showcasing how technology, organizational, and environmental factors interplay with data quality aspects across the lifecycle phases; ranging from data generation, collection, storage, and processing to interpretation and disposal

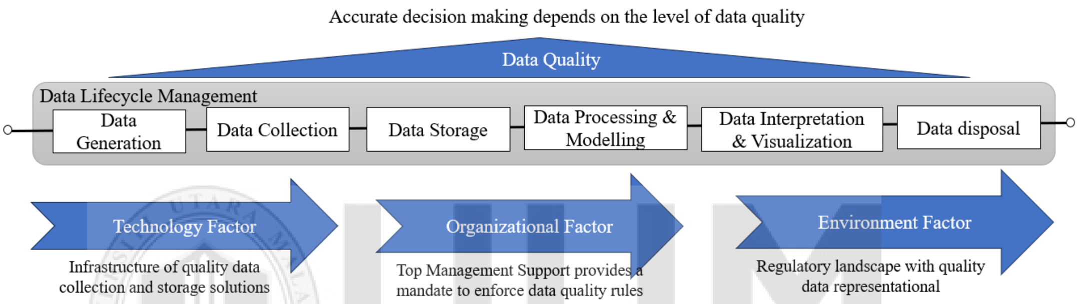

Figure 2.8
Integration of Data Lifecyle Management with TOE Framework, in Relation to Data Quality Aspect

2.5 Data Security

The relationship between data security and organizational performance is crucial. The rapid explosion of data has raised solemn fears about data security (McKinsey, 2018; Amalina et al., 2019; Asif & Hassan, 2023; Falahat et al., 2023), particularly the integrity of sensitive information.

Historically, concerns about the misuse of digital data were already being discussed back in the late 1990s. According to Goriunova and Dekker (1997), the digital data was referred to as "digital media art" back then highlighted how "absurdism" in digital data has been exploited by various groups to further their own agendas. Furthermore, Goriunova and Dekker (1997) suggested that the inherent negativity in modern data absurdism could be misused to promote ideologies that diverge from the original artistic intentions. This raises significant concerns regarding the adoption and misuse of data for political and societal purposes. Martin (2015b), Liu (2021), and Mahmoud et al. (2022) also highlighted the exploitation of data for business benefits, such as the use of secondary data for consumer markets and the challenge of safeguarding personal privacy.

One of the pioneering studies on data security focused on the healthcare industry, where it was noted that medical records were being collected but not adequately protected. In Weaving Technology and Policy Together to Maintain Confidentiality, Sweeney (1997) raised concerns about the delicate balance between technological advancements and the legislative frameworks needed to safeguard confidentiality in digital contexts.

2.5.1 Data Security and Organizational Performance

Data security is a critical aspect of organizational performance, particularly in the era of Big Data adoption. As organizations increasingly rely on data-driven decision-making, the need to protect data from unauthorized access, breaches, and other security threats becomes paramount. Three key sub-factors: Data privacy, security threats, and data breaches will be discussed to evaluate the relationship of data security and organizational performance towards embarking on Big Data adoption.

Data Privacy

Data privacy concerns the protection of sensitive information from unauthorized access and ensuring that personal data is handled in compliance with legal and ethical standards. Anwar et al. (2021) highlighted the challenges of organizations to maintain data privacy while leveraging Big Data technologies. Marr (2018) and (Salleh & Janczewski, 2019) further emphasized the importance of robust data privacy measures in fostering trust among stakeholders and ensuring compliance with regulatory frameworks. In order to gain trust and build customer confidence, organizations must be able to position the data privacy rules better to enhance the organizations' performance by mitigating risks associated with data misuse.

Security Threats

Security threats encompass a range of risks, including cyber-attacks, malware, and other forms of unauthorized access that can compromise data integrity and availability. Kim and Cho (2018), and Mangla et al. (2020a) discuss the evolving nature of cyber threats and the need for advanced security protocols to protect organizational data. The implementation of robust security measures, such as intrusion detection systems and autonomous agents (Mahmood et al., 2020), is crucial in safeguarding against these threats. Effective management of security threats not only protects organizational data but also ensures operational continuity and resilience, thereby enhancing overall performance.

Data Breaches

Data breaches involve the unauthorized access and disclosure of sensitive information, often leading to significant financial and reputational damage. Tao et al. (2019), Ibrahim Ahmed et al. (2023), and Asiri et al. (2024) provide insights into the impact of data breaches on organizations, highlighting the importance of proactive measures to prevent such incidents. The literature indicates that organizations with strong data breach prevention and response strategies can minimize the adverse effects on their performance. By addressing vulnerabilities and implementing comprehensive data security policies, organizations can safeguard their assets and maintain stakeholder trust.

In summary, data security that encompasses data privacy, security threats and data breaches hold pivotal roles in influencing Big Data adoption and organization performance. Organizations that invest in robust data security measures are better equipped to protect their data, ensure compliance, and maintain operational resilience. As the digital landscape continues to evolve, ongoing research and adaptation of security practices will be essential for sustaining organizational performance in the face of emerging data security challenges.

2.6 Ease of Use

Ease of use had been defined as the extent to which a person believes that using a certain technology will be free of effort (Davis, 1989). Similarly, perceived ease of use is described as how well for a user in handling the system and ease of getting the system to do what is required, less mental effort required to interact with the system, and ease of use of the system (Lai et al., 2018; Haddad et al., 2019; Ghaleb et al., 2021; Teoh et al., 2021; Thanabalan et al., 2024).

The ease of use of Big Data technologies is critical for the acceptance and subsequently positively impact on organizational performance. Ease of use relates to how easy people believe a technology is to use. This concept is crucial in the context of Big Data adoption, as sophisticated tools, non-intuitive interfaces, and integration challenges can all impede the effective use of Big Data. This research review investigates the link between ease of use and organizational effectiveness, concentrating on three sub-factors: complex tools, non-intuitive interfaces, and integration challenges.

2.6.1 Ease of Use and Organizational Performance

Complex Tools

The complexity of Big Data Analytics technologies can have a substantial impact on their acceptance and utilization in businesses. Ajah and Nweke (2019), and Ujang et al. (2023) addressed how the complex nature of Big Data tools might present difficulties for users, resulting in resistance and decreased efficiency. Similarly, Asiri et al. (2024) mentioned about necessity of the integration in sustainable technology and Big Data Analytics, because the usage of technologies are frequently hampered by the complexities of the tools. On the other hand, Smith (2023) discussed how organizational factors influence Big Data adoption. The study emphasizes that the complexity of Big Data tools might lead to user resistance, reducing overall adoption and the promised benefits of improved decision-making and operational efficiency.

Non-intuitive

Non-intuitive interfaces are another impediment to the efficient application of Big Data technology. Asiri et al. (2024), and Thanabalan et al. (2024) emphasized that when users find interfaces difficult to traverse, it can lead to frustration, errors, and, ultimately, underutilization of technology. User-friendly interfaces that are simple to comprehend and use are critical for encouraging widespread adoption of Big Data technologies. Organizations may improve the user experience, minimize training expenses, and boost team productivity and performance by building more intuitive interfaces.

Difficult to Integrate

The difficulties that companies have when implementing Big Data technology into their existing systems and workflows are referred to as integration challenges. Dias et al. (2021) and Al-madhrahi et al. (2022) underlined the importance of seamless integration for realizing the full potential of Big Data. When integration is challenging, it can interrupt workflows, create data silos, and limit the availability of insights from Big Data Analytics. Organizations that invest in technologies and procedures that enable seamless integration are better positioned to reap the benefits of Big Data, resulting in improved decision-making and performance.

Overall, while ease of use is a well-known aspect in technology adoption, it remains an important and dependable factor in determining the acceptance and usefulness of Big Data technologies in businesses. Complex technologies, non-intuitive interfaces, and integration issues all provide substantial barriers to realizing the full potential of Big Data. By tackling these difficulties through user–friendly designs, competent training, and seamless integration, organizations can improve their performance and efficacy in Big Data initiatives.

2.7 Top Management Support

Relationship between top management support and organizational performance towards innovation technology such as Big Data adoption is equally important for its successful role in achieving competitive advantage. Top management support is critical to the successful deployment of Big Data technology and improved organizational performance. John P. Kotter, prominent scholar for this subject in the article "Leading Change", emphasizes the importance of strong leadership and dedication from top management in driving change and improving performance (Kotter, 1996).

As organizations increasingly use advanced technology like Big Data Analytics and other digital transformation tools, senior management's influence grows even stronger. Studies have consistently shown that without strong senior leadership support, technology adoption efforts face significant challenges such as insufficient training, low staff motivation, misalignment with strategic objectives, and cultural resistance (Mohamad et al., 2020; Fareed & Su, 2022; Jayeola et al., 2022; Munir et al., 2023).

In the context of Malaysia Digital status companies, resistance to change is a significant barrier in the organizations, where the adoption of new technologies like Big Data requires top management to provide clear communication, consistent training, and a long-term vision to ensure successful implementation. Exploring top management commitment is crucial for achieving organizational goals, as only 'feeling committed' is insufficient (Reza et al., 2021). Several studies underline the importance of top management support for effective implementation and organizational resilience, although research on Malaysia Digital Status companies in Malaysia is limited (Rathina Velu, 2021). This gap is critical because the existing literature focuses on top management's participation in broad contexts, ignoring the unique challenges that Malaysia Digital Status companies face. Understanding how top management support works in such companies is critical for dealing with the practical issues of digital transformation inside a specialized organizational structure (Maroufkhani, Wan Ismail, et al., 2020).

The ability to accept and incorporate Big Data Analytics into organizational operations is critical for creating value and meeting long-term development goals (El-Haddadeh et al., 2021). For example, organizations must not just invest in cutting-edge technology, but also understand how to use it to stimulate creativity and increase performance. This technological readiness is a critical component of effective Big Data adoption.

2.7.1 Top Management Support and Organizational Performance

Understanding the crucial role of top leadership allows organizations to better organize their leadership approaches, maximizing the benefits of technological breakthroughs and driving long-term performance improvements. The following section investigates the link between top management support and organizational effectiveness, concentrating on three sub-factors: Resistance to change, lack of awareness, and integration challenges.

In the context of Global Business Services (GBS) organizations, which frequently use substantial outsourcing models, senior management support is critical for addressing the unique problems associated with Big Data adoption. Many Malaysia Digital Status companies in the GBS sector rely extensively on outsourcing for centralized services including finance, human resources, information technology, and business process outsourcing (BPO) (Global et al., 2024; Ojukwu et al., 2015). This reliance on third-party vendors can have strategic consequences, such as a reduced emphasis on developing internal Big Data capabilities and a misalignment between outsourced solutions and the organization's long-term digital transformation goals (Hanafizadeh & Zareravasan, 2020; Iranmanesh et al., 2023). As a result, top management support is critical for ensuring that outsourcing plans are balanced with in-house projects that strengthen internal data capabilities and correspond with the company's strategic goal for Big Data exploitation. Effective top management engagement may bridge the gap between internal teams and external service providers, fostering greater collaboration and allowing Big Data to reach its full potential adoption (Salleh & Janczewski, 2019; Wahab et al., 2021).

Furthermore, top management's strategic focus is critical in addressing compliance and data sovereignty concerns that frequently arise from outsourcing arrangements, ensuring that the organization follows local regulations and maintains control over its critical data assets goals (Hanafizadeh & Zareravasan, 2020). Integrating strategic supervision into outsourcing decisions can help develop strong data governance frameworks that promote compliance and innovation, leading to a competitive advantage in the GBS industry Varajão et al., 2017.

Resistance to Change

Adoption of new technology, including Big Data, is often hampered by resistance to change. This opposition is frequently motivated by fear of the unknown, disturbance of established workflows, and perceived threats to job security. Hafizal Ishak et al. (2023) highlighted the importance of senior management in overcoming opposition to change by expressing a clear vision and proving the benefits of Big Data efforts. Reyes-Veras et al. (2021) argued that incorporating employees in the planning and implementation phases might lessen resistance and increase buy-in. According to Shahbaz et al. (2019); Egho-Promise & Sitti, (2024) ; Falahat et al. (2023), continuous communication and training are critical for addressing concerns and instilling a positive attitude toward change. Thus, top management must actively interact with employees, give proper training, and maintain open communication to eliminate resistance and support the smooth adoption of Big Data technologies.

Lack of awareness

Lack of awareness about the potential benefits and applications of Big Data is another significant barrier to its adoption. Falahat et al. (2023) noted that many organizations are unaware of how Big Data can enhance their operations and drive competitive advantage. Top management is responsible for educating themselves and their teams about the strategic value of Big Data. Lutfi et al. (2022) highlighted that awareness initiatives, such as proactive sharing (workshops and seminars) and training sessions, can play a crucial role in bridging this knowledge gap. Furthermore, top management should leverage internal and external expertise to build a comprehensive understanding of Big Data capabilities. By fostering an environment of continuous learning and development, top management can ensure that their organization is well-informed about the opportunities presented by Big Data, thereby enhancing its adoption and utilization (Nasrollahi et al., 2021).

Change in Priorities

The changing nature of business environments frequently results in shifts in organizational priorities, which may prevent the sustained focus required for successful Big Data implementation. Falahat et al. (2023) commented that changes in market conditions, competition challenges, and internal strategic realignments can lead to organizations deprioritizing Big Data initiatives. Fareed and Su (2022) underlined the need of top management remaining firm in their commitment to Big Data projects even as priorities shift. According to Lutfi et al. (2022), including Big Data goals into the organization's overall strategic framework can help maintain focus and resource allocation. Similarly, top management should examine and realign their strategic objectives on a regular basis to guarantee that Big Data is still prioritized. By integrating Big Data initiatives into the core strategic agenda, senior management may negotiate changes in priorities without compromising the success and impact of these programs (Zian et al., 2024).

In the perspective Global Business Services (GBS) businesses where outsourcing is common, top leadership in GBS companies frequently shifts their priorities to short-term operational efficiencies through outsourcing rather than long-term digital transformation strategies, deprioritizing internal Big Data initiatives (Hanafizadeh & Zareravasan, 2020; Iranmanesh et al., 2023). This re-prioritization occurs because host organizations commonly outsource the execution of digital transformation to external suppliers, treating it as a secondary function rather than a key strategic initiative. Such an approach may jeopardize the organization's overall Big Data aspirations, as outsourcing arrangements may be incompatible with the broader vision of digital transformation and inhibit the development of internal competences required for ongoing innovation. To enable long-term digital transformation, senior management should balance outsourcing for immediate profits with improving internal capabilities scalability (Hanafizadeh & Zareravasan, 2020; Ojukwu et al., 2015; Varajão et al., 2017).

2.8 Training as a Moderator

Organization needs to provide training program to encourage employees to use innovation more effectively (Majnoor & Vinayagam, 2023; Ujang et al., 2023). The sufficiency of training provided to computer specialists and users of the company will have affirmative effect through the perceived usefulness and perceived ease of use impacting on the adoption of Big Data system directly (Igbaria et al., 1995; Ahmad et al., 2023). Training, system quality and computer experience identified to have a positive connection on perceived usefulness through perceived ease of use. End user computing support had both direct and indirect effect on perceived usefulness, while management support was found to have only an indirect effect. The gap is to evaluate if trainings moderate data quality management, data security, ease of use, and top management support strengthening Big Data adoption. Inadequate training programs remain a critical barrier to successful Big Data adoption. For Malaysia Digital Status companies, the lack of comprehensive and targeted training programs hinders employees from fully utilizing Big Data tools (Chui et al., 2021; Hashim et al., 2021). Given the above-mentioned practical issues and existing theoretical gaps on Big Data adoption, this research was intended to investigate the relationship between abovementioned factors towards Big Data adoption. This research was also intended to examine the moderating values of trainings to emphasize the strengthening or weakening of Big Data adoption for organizations in Malaysia.

2.8.1 Training and Organizational Performance

Training is a fundamental component that significantly influences the adoption of Big Data technologies and enhances organizational performance. Effective training programs ensure that employees possess the necessary skills and knowledge to utilize Big Data tools efficiently, thus maximizing the potential benefits of Big Data initiatives. A study by McKinsey & Company found that organizations may greatly increase their data-driven decision-making processes and overall business performance by investing in staff training and development to increase data literacy and analytical skills (Chui et al., 2021). The following section explores the role of training in Big Data adoption, focusing on its impact on organizational performance through cultivating awareness, and upskilling.

Improve Technical Skills

Training programs targeted to Big Data technologies are critical for providing staff with the skills needed to manage complicated data analysis activities. Baharuden et al. (2019) argued that transformational leadership, paired with targeted training, improved learning intentions and capacities, allowing them to better handle and analyze Big

Data. Similarly, Salleh and Janczewski (2019) highlighted the importance of training that focusing on security best practices and protocols to mitigate risk. This strategy not only enhances individual competencies but also entire organizational performance by encouraging a culture of continual learning and adaptability.

One of the most difficult aspects of Big Data adoption is integrating new technology with old systems. Training programs focusing on best practices for integration are critical. According to Salleh and Janczewski (2019), concerns in Big Data adoption include security and legacy system compatibility. Organizations may ensure a smoother transition and greater utilization of Big Data tools by providing integration training and addressing security concerns, resulting in increased organizational performance.

Build awareness to increase the accountability values

Raising awareness and the values knowledge of new innovative technologies like Big Data is critical for improving organizational performance. For example, training for end users on new technologies are crucial for successful innovation, as demonstrated by the study "Training End Users: An Experimental Investigation of the Roles of the Computer Interface and Training Methods" (Davis & Bostrom, 1993) that highlighted effective training methods can significantly enhance user proficiency and acceptance of new computer interfaces, facilitating the adoption and efficient use of innovative technologies. When employees grasp the potential benefits and applications of Big Data, they are more likely to adopt it, resulting in better decision-making and operational efficiency. Another study emphasized the significance of organizational culture and strategic HR management in facilitating successful adoption and implementation (Ahmad et al., 2023). The moderating influence of training on big data adoption is analogous to the role of Human Resource practices in creating pro-environmental behavior, highlighting that targeted training improves the efficacy of new initiatives by providing employees with the essential skills and mentality. A lack of understanding about the benefits and applications of Big Data could hamper its adoption within an organization. Training programs help to close the knowledge gap. Maroufkhani et al. (2020) asserted the need of teaching to the staff members on the strategic value of Big Data and how it may improve company performance. Ongoing training sessions help to build a full grasp of Big Data, supporting better informed decision-making and boosting the likelihood of successful adoption and implementation. According to Ali (2023), organizations should build a culture of training and maintenance to overcome difficulties such as low productivity and loss of data confidentiality. To ensure training programs are well executed, the support from top management plays pivotal role to engage with the appropriate group for conducting training or provide some incentives to cultivate the staff members to learn new adoptions. As stated by Liao et al. (2023), the top down approach is required to get the buy-in from the working level to participate in training programs.

2.8.2 Training as Moderator

A moderating variable is an interacting term which emerges when the relationship between independent and dependent variables is surprisingly weak, inconsistent, or non-existent. The moderating variable is introduced to strengthen or weaken this relationship (Baron & Kenny, 1986; Sekaran & Bougie, 2009). Moderators can be either qualitative or quantitative, such as gender, race, or level of awareness, and may help explain variations in outcomes (Baron & Kenny, 1986).

According to the Resource-Based View (RBV), training can be regarded a significant organizational resource, improving the company's capacity to use Big Data technologies for long-term competitive advantage (Barney, 1991). While the Technology-Organization-Environment (TOE) framework emphasizes the importance of organizational readiness, the literature shows a gap in understanding how training influence the impact, as a resource, Hence, this study needs deeper exploration into the role of training in technology adoption aligns with the broader understanding of training itself (Baharuden et al., 2019; Al-Rahmi et al., 2019; Chuah & Thurusamry, 2021; Harun et al., 2022; Thanabalan et al., 2024).

Beardwell and Claydon (2007) define training as a set of activities focused on present needs, aiming to build future capabilities and enhance organizational potential. However, training does not always result in improved performance. It can sometimes have a minimal or negative effect, especially if it becomes outdated due to a lack of continuous support or adaptation to new skills (Akter et al., 2016; Mahmood et al., 2023).

Figure 2.9 presents the Ecosystem of Big Data Solutions, highlighting the relationship between critical factors such as Data Quality, Data Security, Ease of Use, and Top Management Support, all moderated by Training. This figure summarizes the data flow and analytics capabilities that directly contribute to improved organizational performance through operational efficiency, market value and competitive advantage.

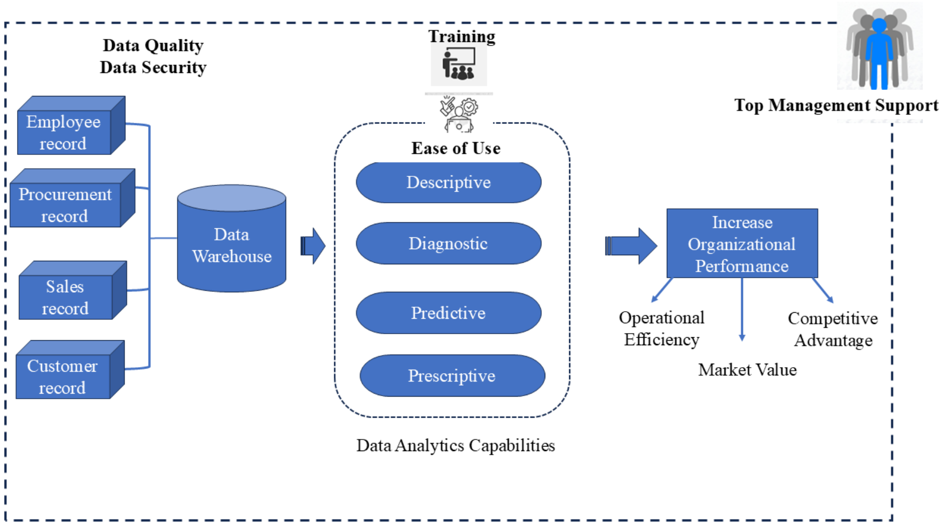

Figure 2.9
Ecosystem Big Data Solutions

2.9 Underpinning Theories

2.9.1 Technological-Organizational-Environmental Framework (TOE)

Tornatzky and Fletscher (1990) developed the technology-organization-environment (TOE) framework to describe the multiple elements influencing an organization's decision to adopt new technologies. The TOE framework outlines how the adoption of technological innovations is influenced not only by the technology itself but also by organizational characteristics and external environmental factors. The multiple elements influencing an organization's decision to adopt new technologies. The TOE framework describes how organizational features and external environmental factors influence the adoption of technical advancements, as well as the technology itself. The framework's three key components; technology, organization, and environment provide a comprehensive view of adoption processes by addressing both internal and external factors that influence the integration and use of technology in organizational settings (Hashim et al., 2022; Salleh, 2016; Zhu et al., 2003).

Technological Context

The technical context refers to the accessible technologies that are useful and possibly advantageous to an organization, taking into account both internal and external technology resources. In the context of Big Data adoption, data quality control and usability are essential technological elements. Data quality is critical for proper analysis and decision-making since faulty data can lead to incorrect insights, thereby impacting business outcomes (Shanmugam et al., 2023). In contrast, ease of use is critical for guaranteeing user acceptability and seamless adoption of Big Data systems, as user-friendly interfaces improve accessibility and reduce training needs (Parulian et al., 2023; Shanmugam et al., 2023). Previous research has emphasized the relevance of accessible and dependable technology in effective innovation adoption (Cao et al., 2014; Zian et al., 2024b).

Organizational Context

The organizational context focuses on an organization's resources, structure, and culture, which all influence its ability to adopt new technology. Top management support for Big Data adoption is an important organizational component because it influences strategic direction, resource allocation, and overall commitment to innovation (Tabesh et al., 2019). Senior leadership support guarantees adequate resource allocation and fosters an innovative culture. According to studies, without strong management support, organizations may struggle to match technological adoption with business goals, limiting successful implementation (Wahab et al., 2021).

Environmental Context

The environmental context takes into account the external elements that influence technology adoption, such as regulatory demands, competition, and industry trends. Data security is an important environmental issue, particularly in Big Data adoption, because companies must fulfil external legal obligations while also managing risks from cyber threats (Anawar et al., 2022). Prior study has shown that companies must comply with data protection rules and develop methods for dealing with external security threats in order to maintain data integrity and customer trust (Egho-Promise & Sitti, 2024; Y. Liu, 2021; Salleh & Janczewski, 2019).

Numerous empirical research have used the TOE framework to investigate technological adoption across industries, confirming its usefulness as depicted in Table 2.5. (Ghaleb et al., 2023; Lai et al., 2018; Maroufkhani, Wan Ismail, et al., 2020). This study broadens the TOE framework to assess Big Data adoption by focusing on data quality management, ease of use, top management support, and data security as depicted in Figure 2.10.

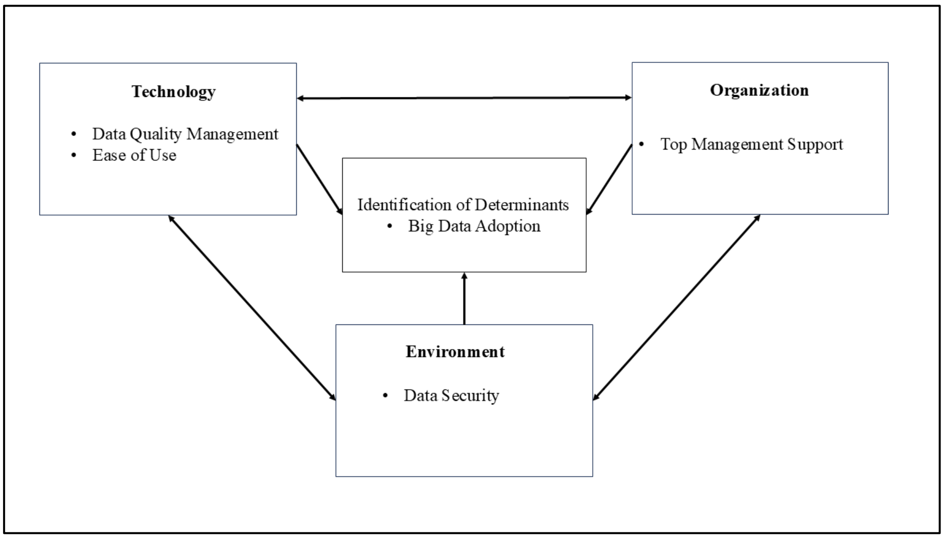

Figure 2.10
Technology, Organization and Environment (TOE) Framework

Table 2.5
Underpinning Theories

Factors	(Zian et al., 2024)	(Vachkova et al., 2023)	(Ibrahim Ahmed et al., 2023)	(Ghaleb et al., 2023)	(Atan, 2022)	Wahab et al. (2021)	Salleh and Janczewski (2019)
Technology	Complexity and compatibility. Lack of skills and talent.	Compatibility. Relative advantage	Complexity. Relative Advantage. Security and Privacy. Compatibility	Complexity. Compatibility. Relative Advantage. Optimism. Innovativeness	Relative Advantage. Compatibility	Relative Advantage.	Data collection
Organization	Top management support. Financial capability. IT infrastructure.	Organizational readiness. Top management support	Skills. Top management support. Financial readiness. Firm size	Nil.	Top management support. Organizational readiness	Technological infrastructure. Absorptive capability.	Top management support. Education, training, and awareness. Personnel skills and experience. Employee perception
Environment	Legal challenges. Government regulations.	Critical mass. Competitive pressure	Competitive pressure. Government support. Market turbulence.	Nil.	Competitive pressure. Competition intensity. Information intensity. Government support	Industry competition. Government support.	Regulatory compliance. Reputation of vendor. Environmental uncertainties.

2.9.2 Resource Based View Theory

Resource-based view theory is a model that identifies resources as fundamental factors of company's performance and competitive advantage. Resources are defined as "anything which could be thought of as a strength or weakness of a given organization" (Wernerfelt, 1984). An organization's resources could be defined as tangible and intangible assets which are secured to the organization. Wernerfelt et. al (1984). added the example of resources such as brand names, in-house knowledge of technology, employment of skilled personnel, trade contacts, machinery, efficient procedures, capital etc. The theory indicates that a resource has to be valuable that is it must enable an organization to employ a value creating strategy by being rare and inimitable (Barney, 1991b). And for the perspective of this study, the intangible assets such as human capital that expand to worker's skills, experience, and knowledge are intangible assets that are essential for innovation and operational efficiency. Organizations that can attract, retain, and develop high skilled- personnel typically have a competitive advantage.

RBV was chosen to represent training as intangible assets which create the strength to organizations. Training is an important aspect in the RBV framework since it improves an organization's workforce capabilities and competencies. Effective training programs can transform ordinary resources into strategic assets by boosting employees' skills and knowledge, increasing the firm's ability to optimize resource utilization (Garavan, 2020).Training provides staff workers with the skills needed to properly use Big Data Analytics technologies, which may transform raw data into valuable insights. Knowledge Enhancement: Continuous learning initiatives keep staff up to date on the newest technology breakthroughs, which promotes innovation and efficiency. Capability Building: Training enhances employees' ability to conduct complex analyses and make data-driven decisions, aligning with the firm's strategic goals. Relationship Between Training, Big Data, and Organizational Performance Training serves as an important moderator in the relationship between Big Data adoption and organizational success. Big Data has a major impact on performance when staff are well-trained and proficient in using Big Data tools and technology. This alignment is critical for various reasons.

2.10 Research Framework

The research framework developed in this study combines the Technology-Organization-Environment (TOE) framework with the Resource-Based View (RBV) theory to account for both external and internal factors impacting Big Data adoption. The TOE paradigm is ideal for investigating how external demands (such as regulatory compliance and competitive intensity) interact with organizational preparedness and technology infrastructure (Tornatzky & Fletscher, 1990). This provides a systematic way to analyze the external elements (technology, organization, and environment) that either enable or impede Big Data adoption. In parallel, the RBV theory emphasizes the strategic importance of internal resources, notably training, which can transform organizational capacities and facilitate effective technology integration (Barney, 1991). By emphasizing training as a critical resource, the RBV emphasizes its role in increasing the organization's absorptive capacity, hence strengthening its ability to use Big Data for better performance outcomes.

This integration provides a comprehensive perspective that successfully tackles the complex interaction of internal and external forces. For example, data quality management and ease of use fall under the technological dimension, whereas top management support is defined as an organizational element and data security as an environmental factor. Recent research Lutfi, Al-Khasawneh, et al. (2022) has validated the effectiveness of TOE and RBV frameworks in explaining complex adoption scenarios, demonstrating how external determinants such as competitive intensity and regulatory pressures can be mitigated by strong internal capabilities, particularly through targeted training interventions. The conceptual model thus demonstrates the optimal integration of TOE and RBV features, resulting in a solid framework for understanding Big Data adoption and its impact on organizational performance.

The integration of these theories is consistent with the study's focus on Global Business Services (GBS) organizations in Malaysia, which frequently confront unique issues in balancing global operational demands and local regulatory duties (Bernama, 2022). By include training as a moderating variable, the model fills a major research gap by demonstrating how it can magnify or attenuate the effects of identified determinants (for example, low ease of use or poor top management support) on performance. This method offers practical insights into how organizations can strategically employ both internal and external resources to improve Big Data adoption success.

The framework integrates the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV) theory to investigate how variables that deemed to be barriers of Big Data adoption affect organizational performance. The

TOE framework identifies major drivers in three dimensions (technology, organization, and environment), whereas the RBV theory emphasizes the strategic value of internal resources, that is training. For this study, training implies Big Data Analytics training.

Integration of TOE Framework and Resource Based View

The TOE framework has a substantial impact on Big Data adoption in numerous areas. Studies have demonstrated that technology, organization, and environment can all have a major impact on Big Data adoption mainly in SME, healthcare, manufacturing, financial and other agencies (Anawar et al., 2022; Ghaleb et al., 2021; Harun et al., 2022; Hashim et al., 2022; Ibrahim Ahmed et al., 2023; Kamarulzaman & Hassan, 2019b; Lutfi, Al-Khasawneh, et al., 2022; Maroufkhani, Wan Ismail, et al., 2020; Wahab et al., 2021; Zhu et al., 2003; Zian et al., 2024b).

The integration of TOE and RBV illustrate optimal combination for the factor of technology, organization and environment towards innovation adoption and RBV represents precisely the internal resources of human resources as key enabler to increase the success of Big Data adoption in organizations.

The integration of TOE and RBV creates the holistic view that covers the element of external (technology, environment) and internal (organization, training) factors. Data quality management and ease of use are grouped under technology, top management support is part of organization and security is considered under environment. Big Data Analytics training serves as a moderating variable, increasing the impact of TOE components on organizational performance.

Figure 2.11 represents the view of research framework for this study. Figure 2.12 depicts a complete framework for investigating the factors that influence Big Data adoption, with a focus on three core domains: technology, organization, and environment, each of which contributes to corporate success. It also emphasizes the moderating impact of training in improving these contributions. Finally, Table 2.6 summarizes limitations and contributions, provides a detailed comparison of limitations from previous studies and the contributions made by the current research.

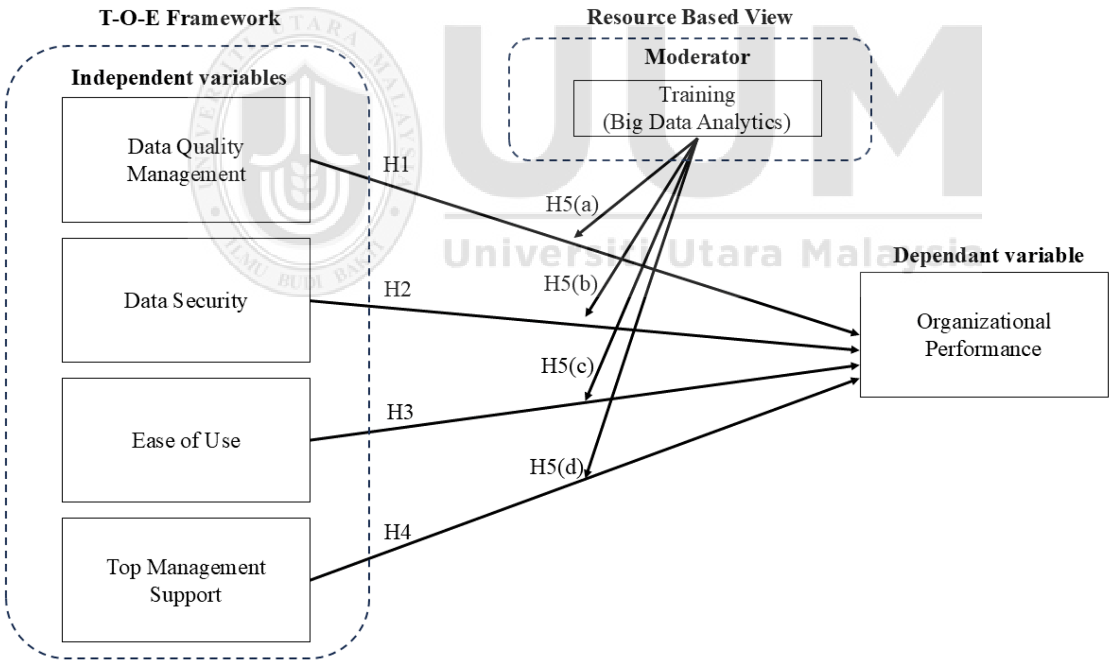

Figure 2.11
Proposed Research Framework

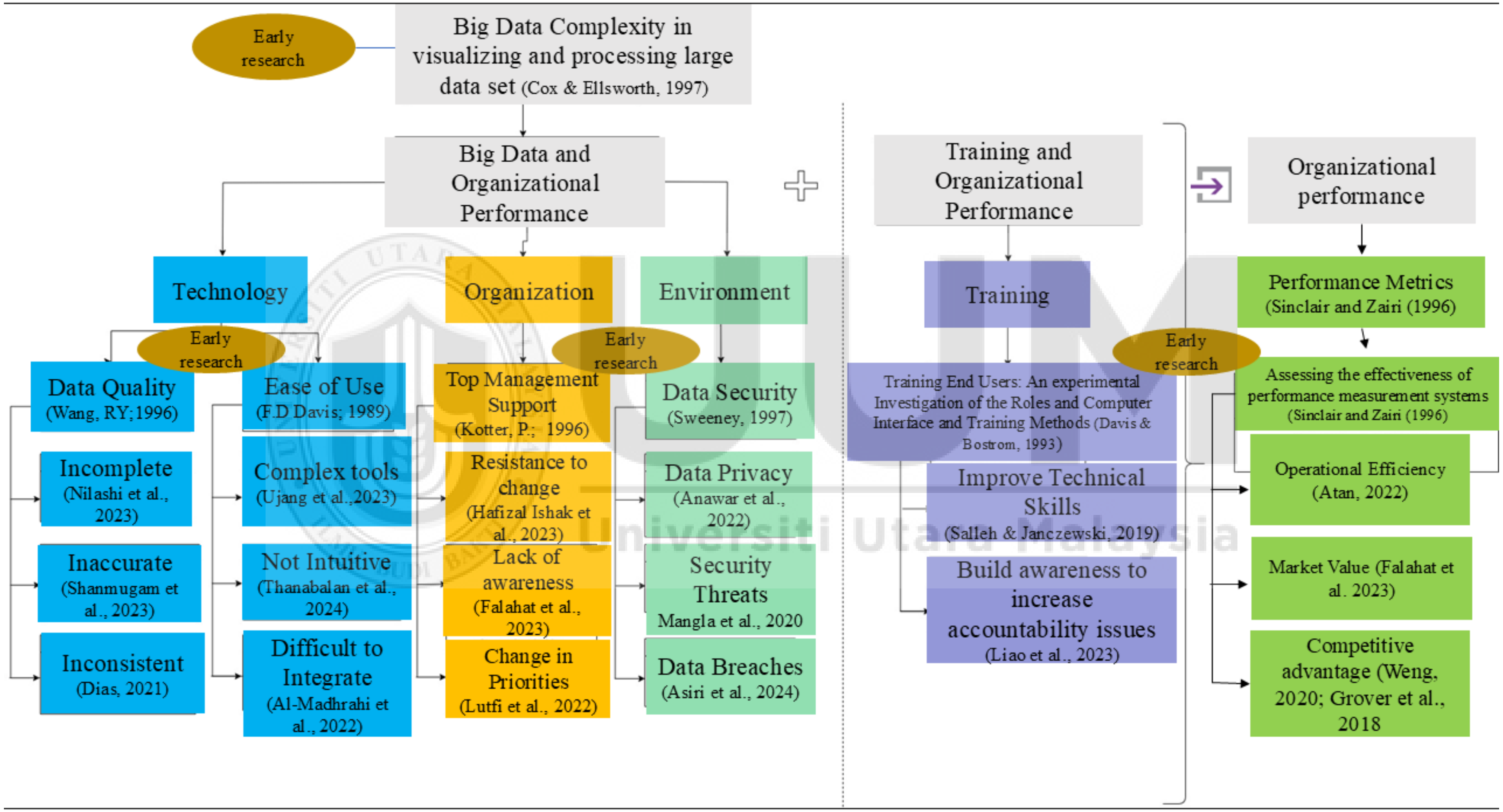

Figure 2.12

Comprehensive Overview of Research Gaps, New Foundation of Knowledge and Acknowledgement of Previous Researchers

Table 2.6

Summary of Limitations and Contributions

Component	Limitations from previous studies	Limitations of researcher's study	Contributions of researcher's study
Confusion about Big Data Definition	Inconsistent definition of Big Data leading to confusion as there were limited historical perspective and research regarding the Big Data (Volk et al., 2022).	The study provides the historical timeline of Big Data but does not address the reasoning about the confusion of the definition.	A comprehensive overview of Big Data definitions and the evolution through structured timeline are described in the current study.
Phases of Data Analytics	Lack of understanding of Big Data and connectivity with Deep Learning, Machine Learning and Artificial Intelligence (Chen, Chiang, & Storey, 2012; Davenport, 2016).	The differences are explained briefly but not extensively.	Developed connection ring to illustrate the subset connection between Big Data, deep learning, machine learning and artificial intelligence to give better understanding as the term is commonly interchangeable by one another.
Big Data Adoption in Malaysia Landscape	Previous studies in Malaysia contexts were mainly focused on SME industry (Baharuden et al., 2019; Zian et al., 2024).	Specific focus on company portfolio that is Malaysia Digital Status companies.	One of the few studies that focusing on Big Data Adoption in Malaysia Digital Status Companies.
Data Quality Management	Less attention about data quality being discussed in the context of Big Data Adoption (Ghaleb et al., 2021; Mahdi Nasrollahi, Javaneh Ramezani, 2021).	The discussion for data quality in bigger perspective and cross industry may not be fully explored.	Constructive framework developed in the study to illustrate the impact data quality in the uptake of Big Data Adoption.
Data Security	Limited studies pertaining to data security aspect with intervention of training to increase adoption (Salleh, 2016; Kamarulzaman & Hassan, 2019).	The research is only limited to specific portfolio of the companies that is the scope is only for Malaysia Digital Status Companies and using quantitative method. Limited view through qualitative data to understand user perspectives and the practical challenges	Integrate the role of training in enhancing data security measures and Big Data adoption. Surface the

Table 2.6 (Continued)

Component	Limitations from previous studies	Limitations of researcher's study	Contributions of researcher's study
Ease of Use	Many studies emphasize the technical aspects of Big Data adoption without considering the practical (Baig et al., 2019; Maroufkhani et al., 2020).	The research is only limited to specific portfolio of the companies that is the scope is only for Malaysia Digital Status Companies and using quantitative method. Limited view through qualitative data to understand user perspectives and the practical challenges	Demonstrates the positive impact of user–friendly Big Data tools on organizational performance, through comprehensive training modules.
Top Management Support	Previous research frequently focused on theoretical frameworks without extensively test practical applications and the effect of top management support on Big Data adoption (Haddad et al., 2019; Ghaleb et al., 2021; Alyoussef & Al-Rahmi, 2022; Falahat et al., 2023; Asiri et al., 2024).		Integrate the role of training to measures the direct and indirect with Big Data adoption with several aspects of data quality management, data security, ease of use and top management support.

2.11 Hypothesis Development

To help support the hypotheses, this study combines two major theoretical frameworks: the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV) theory.

The TOE framework (Tornatzky & Fletscher, 1990) divides essential factors influencing technology adoption into three categories: technological, organizational, and environmental contexts. The TOE framework is used in this study to classify data quality, data security, ease of use, and top management support as determinants in various scenarios. These determinants are seen as critical for successful Big Data adoption.

The RBV hypothesis (Barney, 1991) highlights the need of using internal resources to gain a competitive advantage. This study emphasizes on training as an important internal resource, arguing that it mitigates the impact of TOE factors on organizational performance. Training improves an organization's absorptive capacity, or ability to perceive, digest, and use external knowledge efficiently, hence increasing Big Data capabilities and performance.

The merging of these two theories is consistent with current studies. For example, Lutfi, Al-Khasawneh, et al. (2022) emphasizes the significance of a comprehensive approach to understanding both internal (RBV) and external (TOE) elements that influence Big Data adoption and performance outcomes. These studies highlight the importance of a complete approach that includes both external technology elements and internal resources in improving organizational performance during digital transformation.

2.11.1 Relationship of Data Quality Management and Organizational Performance

High-quality data is necessary for reliable analysis and decision-making, which includes not just accuracy but also relevance, completeness, timeliness, and accessibility. Without these quality characteristics, companies may have erroneous insights, leading to operational inefficiencies and poor strategic decisions (Ghasemaghaei & Calic, 2019; Wook et al., 2021 ; Nilashi et al., 2023). Several studies have demonstrated the harmful impact of poor data quality on organizational performance. For example, limited data may lead to information irregularity, resulting in a lack of transparency and higher risk in decision-making (Solana-González et al., 2021). Similarly, inaccurate data disrupts operational efficiency, leading to increased expenses as companies struggle to remedy inaccuracies (Onyeabor & Ta'a, 2018 ; Shanmugam et al., 2023). Inconsistent data complicates these challenges by impeding data integration efforts, resulting in poor decision-making and strategic misalignment (Dias et al., 2021; Nilashi et al., 2023).

The Technology-Organization-Environment (TOE) Framework views data quality as a critical technological factor impacting organizational performance. High-quality data allows for more accurate, relevant, and timely decisions, increasing operational efficiency and strategic effectiveness (Ghasemaghaei & Calic, 2019 ; Nilashi et al., 2023). The TOE framework identifies this technology component as critical for harnessing Big Data capabilities to create higher performance outcomes (Tornatzky &

Fletscher, 1990). Data quality management ensures data integrity, completeness, and accuracy, which are critical for high-performing organisations. This is consistent with the TOE paradigm, in which data quality as a technological aspect has a direct impact on the organization's ability to get insights and improve performance (Dias et al., 2021).

Given the importance of data quality in achieving operational and strategic results, and in line with the TOE framework's emphasis on technological readiness, we believe that companies with higher degrees of data quality management will perform better.

From the discussion, the research summarizes that there is positive relationship of Data Quality Management and Organizational Performance. Based on the above discussion, the researcher makes the following proposition:

H1: Significant positive relationship between data quality management and organizational performance.

2.11.2 Relationship of Data Security and Organizational Performance

The rapid increase in data usage in organizations has raised worries about data security (Amalina et al., 2019; Anwar et al., 2021; Asif & Hassan, 2023;Falahat et al., 2023), notably the protection of sensitive information. Data security's function in ensuring data integrity, confidentiality, and availability is critical to sustain organizational trust, compliance, and operational resilience. Sweeney (1997) was a pioneer in highlighting the critical issue of data security in public health, emphasizing the healthcare sector as an early example of the delicate balance between technological innovation and legislative measures to ensure data protection. This perspective is further supported by Dias et al. (2021) ; Fatt & Ramadas, (2018).

For Data Privacy, protecting personal and sensitive data is critical for building confidence with stakeholders and maintaining compliance with legal and ethical norms (Anwar et al., 2021; Marr, 2018; Salleh & Janczewski, 2019). Cyber-threats, malware, and illegal access are serious threats to data security, with the potential to compromise data integrity and disrupt operations (Salleh & Janczewski, 2019; Kim & Cho, 2018). Effective security threat management protects organizational data while also ensuring continuity and resilience. Companies with excellent data breach prevention and response procedures get better performance outcomes (Tao et al., 2019; Ibrahim Ahmed et al., 2023; Asiri et al., 2024).

Data security is classified under environmental factor in the TOE Framework because of the demand of compliance with external regulations, data protection legislation, and controlling external cyber risks (Anawar et al., 2022). As businesses implement Big Data technology, the requirement to protect data from breaches and illegal access becomes increasingly important for ensuring operational resilience and stakeholder trust.

From the discussion, the researcher makes the following propositions:

H2: Significant positive relationship between data security and organizational performance.

2.11.3 Relationship of Ease of Use and Organizational Performance

F. D. Davis (1989) highlighted that perceived ease of use significantly impacts an individual's decision to accept and use technology. This concept has since expanded to encompass the user's perception of how easy it is to interact with a system, perform activities with minimal mental effort, and achieve desired outcomes efficiently (Haddad et al., 2019; Ghaleb et al., 2021; Teoh et al., 2021; Thanabalan et al., 2024).

Ease of use affects organizational effectiveness through a variety of factors. For starters, user-friendly solutions eliminate the need for extensive training, increases the speed of adoption, leading to cost savings for organizations (Mohamad et al., 2020). Second, when users find a system straightforward, they are more likely to use it to its full potential (Smith, 2023). Third, ease of use can increase employee productivity by reducing the cognitive burden and effort required to interpret data, allowing for faster and more effective decision-making (Asiri et al., 2024).

Within the TOE framework, ease of use represents a critical technological determinant that positively influences the successful implementation of Big Data solutions. It ensures that the technology is not only accessible but also aligns with user needs, ultimately leading to improved organizational performance, thereby strengthening their competitive position (Ajah & Nweke, 2019; Ujang et al., 2023).

From the discussion, the researcher makes the following propositions:

H3: Significant positive relationship between ease of use and organizational performance.

2.11.4 Relationship of Top Management Support and Organizational Performance

Top management support is crucial in establishing good organizational performance, especially when it comes to adopting innovative technologies like Big Data. Kotter, (1996), a renowned scholar on change management, underlined the importance of effective top-level leadership in driving change and enhancing performance.

Top management engagement involves providing a clear vision, allocating required resources, and cultivating a culture that values risk-taking and continual learning (Mohamad et al., 2020 ; Fareed & Su, 2022). Without this degree of support, companies frequently encounter issues such as insufficient training, low employee enthusiasm, misalignment with strategic goals, and cultural resistance to change (Schroeck et al., 2012; El-Haddadeh et al., 2021). Furthermore, McAfee & Brynjolfsson (2012) and Mikalef & Gupta (2021) stated that in order to properly exploit Big Data, top management must address concerns including as leadership, human management, technological capabilities, decision-making, and business values.

This aligns with the TOE framework, which is classified under the organization context, suggesting that effective top management support facilitates resource allocation, alignment of strategic objectives, and resolution of resistance to change (Mikalef & Gupta, 2021).

From the discussion, the researcher makes the following propositions:

H4: Significant positive relationship between top management support and organizational performance.

2.11.5 Moderating Role of Training with determinants (Data Quality Management, Data Security, Ease of Use, Top Management Support) and Organizational Performance

Training plays a crucial role in facilitating Big Data adoption and enhancing organizational performance. It empowers employees with the skills and knowledge needed to utilize Big Data technologies effectively, fostering improved decision-making and operational efficiency (Talukder, 2012; Igbaria et al., 1995). While training is often perceived as a direct influencer of technology adoption, its role as a moderating factor between Big Data adoption and organizational performance remains underexplored, particularly within the context of Malaysian organizations (Baharuden et al., 2019 ; Al-Rahmi et al., 2019).

The relationship between training and organizational performance is well-established to. Chui et al. (2021) highlights that organizations investing in training can enhance data literacy and analytical skills, thus leading to improved performance outcomes. Training improves technical skills (Baharuden et al., 2019), helps navigate complexities in system integration (Salleh & Janczewski, 2019), and builds awareness to foster accountability and informed decision-making (Maroufkhani, Wan Ismail, et al., 2020). However, it is also noted that training may not always result in positive outcomes due to potential issues such as outdated content and lack of continuous support (Thanabalan et al., 2024). The study raises the question of how inadequate training in large companies affects the outcome of Big Data adoption.

In the perspective of the Resource-Based View (RBV), training is an investment in human capital that improves organizational capacities. Training improves the organization's absorptive capacity, allowing it to better integrate new technology into current systems and procedures. With that, the hypothesis aims to explore whether effective training can amplify the positive effects of key determinants by enhancing employees' ability to utilize Big Data solutions more effectively.

From the discussion, the researcher makes the following propositions:

H5(a): Training significantly moderates the relationship between data quality management and organizational performance.

H5(b): Training significantly moderates the relationship between data security and organizational performance.

H5(c): Training significantly moderates the relationship between ease of use and organizational performance.

H5(d): Training significantly moderates the relationship between top management support and organizational performance.

2.12 Summary

This chapter provides a comprehensive literature review of the determinants influencing Big Data adoption and its influence on organizational performance. The underpinning theory of the TOE framework and RBV highlights the context of technology, organization, and environment, along with internal resources such as organizational capabilities and training, interact to drive successful adoption. Table 2.7 provides the mapping of Research Question, Research Objectives and Hypothesis.

Table 2.7
Research Question, Research Objective, Hypothesis

Research Question	Research Objective	Hypothesis
RQ1 :What is the relationship of data quality management in Big Data adoption and organizational performance.	**RO1**: To examine the relationship between data quality management in Big Data adoption and organizational performance.	**H1:** Significant positive relationship between data quality management and organizational performance.
RQ2 :What is the relationship of data security in Big Data adoption and organizational performance.	**RO2**: To examine the relationship of data security in Big Data adoption and organizational performance.	**H2:** Significant positive relationship between data security and organizational performance.
RQ3 :What is the relationship of ease of use in Big Data adoption and organizational performance.	**RO3**: To examine the relationship of ease of use in Big Data adoption and organizational performance.	**H3:** Significant positive relationship between ease of use and organizational performance.

Table 2.7 (Continued)

Research Question	Research Objective	Key variables/Concept
RQ4: What is the relationship of top management support in Big Data adoption and organizational performance.	**RO4**: To examine the relationship between top management support in Big Data adoption and organizational performance.	**H4:** Significant positive relationship between top management support and organizational performance.

Table 2.7 (Continued)

Research Question	Research Objective	Key variables/Concept
RQ5 :What is the moderating effect of training on the relationship of data quality management, data security, ease of use, and top management support in Big Data in increasing organizational performance.	**RO5**: To examine the moderating effect of training on the relationship of data quality management, data security, ease of use, and top management support in Big Data adoption and its impact in increasing organizational performance.	**H5(a):** Training significantly moderates the relationship between data quality management and organizational performance. **H5(b):** Training significantly moderates the relationship between data security and organizational performance. **H5(c):** Training significantly moderates the relationship between ease of use and organizational performance. **H5(d):** Training significantly moderates the relationship between top management support and organizational performance.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

Methodology refers to the principles and philosophy of the assumptions that have been made and it led to the selection of studies to be made. Usually, this can be described by several major literatures included in the methodology of the researchers. This section covers and determines which method is used by the researcher. Research methodology is a collection of simple methods to conduct research; It is an effective way to solve the problem of the study. In accordance with Kothari, Shanken and Sloan (1995), research methods refer to the strategies and techniques used by researchers in the matter of a review. Examples are the techniques of data collection, processing techniques and instruments.

3.2 Research Methodology Flow Chart

This study is correlational in nature, as the major goal was to investigate the impact of variables proposed to influence organizational performance. Correlational analysis was utilized while trying to explore causal correlations between variables (Zikmundet al., 2010; Sekaran & Bougie, 2013). This study examined the relationship between each factor of data quality management, top management support, data security, ease of use, training, and organizational performance. It is also confirmatory in nature, as data were collected cross-sectionally, and all variables were examined simultaneously. The next subsections describe in detail the research approach, demographic and sampling procedure, data collection procedure, research instrument, pilot study, and statistical analysis utilized to evaluate the hypotheses. This research's field study was done in a non-contrived setting, with data collected via a self-administered questionnaire on the factors under consideration. Figure 3.1 depicts the many stages and processes of the research technique.

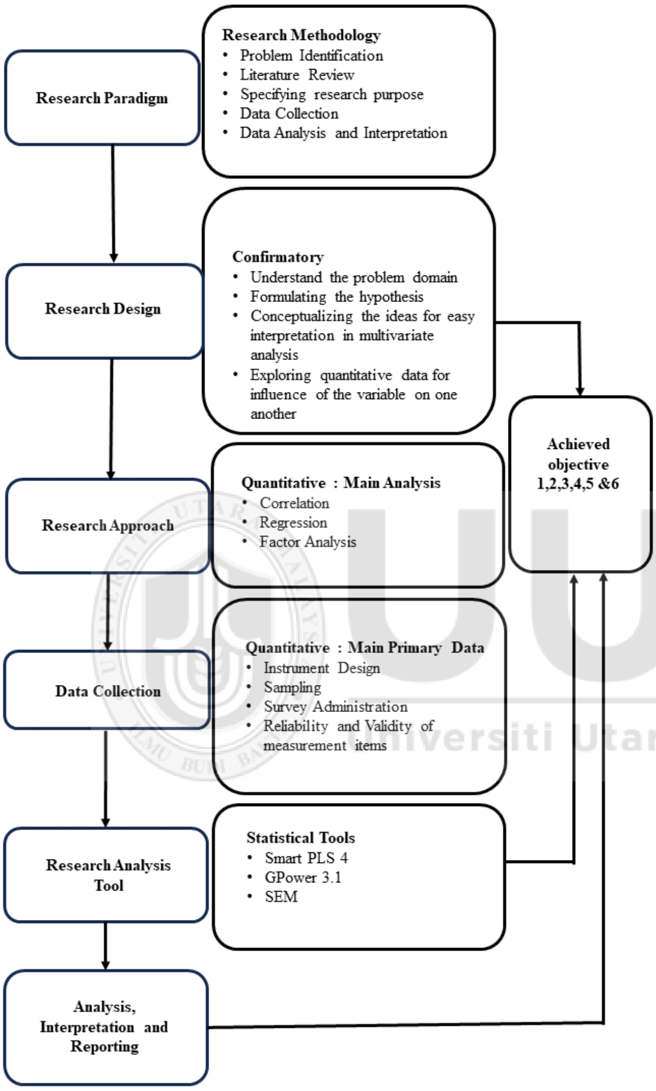

Figure 3.1
Research Methodology Flow Chart

3.3 Research Design

According to Zikmund (2003), the study design is a principal plan that outlines the techniques and processes for collecting and analyzing the necessary information.

Therefore, it is a crucial step in the study. The descriptive research approach is appropriate for this study since it seeks to find the links between the variables that influence Big Data adoption and organizational success. This design enables for the methodical collection of exact information, resulting in a thorough grasp of the difficulties facing by companies (Saunders et al., 2015). Descriptive research provides a clear picture of how these issues influence the adoption process by capturing the characteristics and relationships between variables (Bhattacherjee, 2012).

According to Creswell (2007) the descriptive design will assist in presenting data regarding the nature and condition of the situation as it existed at the time of research. The design will also depict existing relationships and behaviors, ongoing beliefs and processes, perceived effects, and emerging trends. Thus, this study employed the descriptive design to analyze and explain attitudes and remarks about Big Data usage in Malaysia. The study’s design was appropriate because it allowed for data gathering with minimal variable manipulation.

3.3.1 Research Design Framework

Research design is a framework that provides guidelines for collecting and analyzing data to address the study's hypothesis. According to Zikmund (2003), the study design is a master plan that outlines the techniques and procedures for gathering and analyzing the necessary information, making it a crucial component of research. Additionally, Burns & Grove (2007), assert that research design is a step toward understanding meaningful phenomena in specific situations.

According to Creswell (1998), the descriptive design will help to present facts about the nature and status of the situation as it exist at the time of study. This design will portray the relationship and practices that exist, beliefs and processes that are on-going, as well as effects that are felt and trends which are developed. The study used the descriptive design to provide analysis and an explanation of opinions and comments concerning Big Data adoption in Malaysia. The design was appropriate for the study since it enabled collection of information with minimum manipulation of variables. The methodology framework of the overall research design is illustrated in Figure 3.2.

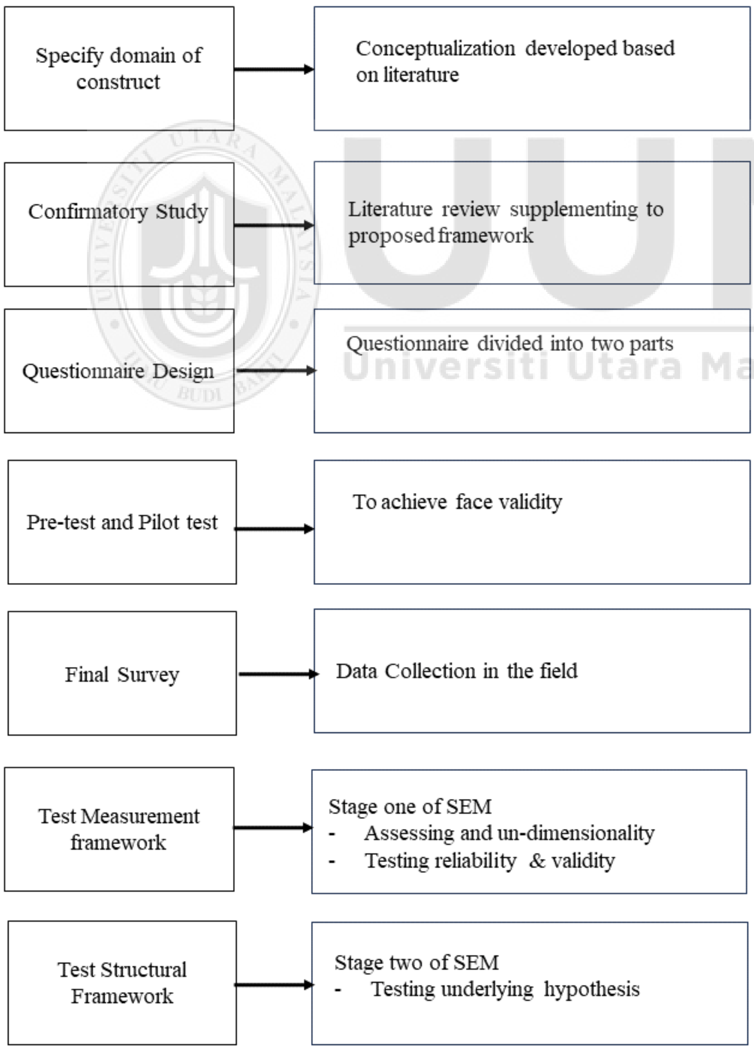

Figure 3.2
Overview of Methodology in this Research

3.3.2 The Qualitative Design

Alternatively, according to Creswell (1998), qualitative research is a type of inquiry in which the researcher creates a complex, holistic picture by analyzing language, reporting detailed viewpoints of informants, and conducting the study in a natural context. According to Guba and Lincoln (1982), in this method, the researchers argue knowledge-based constructivism, or a solid worldview. According to Mertens (2003), a collection of information were acquired from them in their everyday lifestyle context in which the study is framed, and data analysis is dependent on the values of these participants for their world perspective. Finally, Creswell and Miller (2000) stated that it generates an understanding of this topic through a variety of contextual elements.

3.3.3 The Quantitative Design

According to Sekaran (2003b), quantitative design is defined as analyzing data or information that is descriptive. However, Marczyk et al. (2005) asserted that quantitative study is a study that involves the use of statistical analysis to get results. Meanwhile, Gay et al. (2012) stated that a good sample for quantitative research is samples that can represent the population from which it is selected.

According to the preceding discussions, in this study, researchers distributed the questionnaire using a quantitative design technique because it is based on a literature review. According to Sekaran (2003), questionnaires are the most prevalent method of data collection since researchers may get relatively straightforward information and the answers to the questionnaire are merely indicated.

3.3.4 Moderator vs Mediator

Moderation and mediation analyses are statistical approaches commonly employed in the realm of causal inference. However, they each fulfil separate objectives and possess unique attributes. It is crucial to comprehend the similarities and distinctions between these two strategies in order to select the suitable way.

Mediation analysis was used to explore the causal route by which an independent variable (IV) influences a dependent variable (DV) through an intermediate variable known as a mediator (Baron & Kenny, 1986). The goal of mediation analysis is to understand the mechanisms and reasons for the influence of the independent variable (IV) on the dependent variable (DV) (Hayes, 2022). This was performed by looking at the mediator variable. Researchers frequently use structural equation modeling (SEM) to conduct mediation analysis, with the goal of determining the causal relationship between the independent variable (IV) and the dependent variable.

Moderation analysis determines the strength or weakness of the link between the independent variable (IV) and the dependent variable (DV) (Baron & Kenny, 1986). Moderation analysis aims to determine how a separate variable (referred to as the moderator) effects the connection between the independent variable (IV) and the dependent variable (DV) (Hayes, 2022). Moderation analysis usually employs multiple regression analysis to study the precise timing and manner in which the independent variable (IV) influences the dependent variable (DV) (Toothaker et al., 1994).

For this research area, moderator is the best fit model to use as it is examining the result of IV and DV whether it's strengthened or weakened between both IV/DV. Furthermore, there is similar research on Big Data adoption which adopted training or learning intention as moderating factor to evaluate the impact on organizational performance (Lutfi et al., 2022; Soon et al., 2016).

3.3.5 Unit of Analysis

The unit of analysis for this study comprises organizations with Malaysia Digital Status, specifically those classified as Global Business Services (GBS) cluster. The data was collected from 428 GBS companies registered with the Malaysia Digital Economy Corporation (MDEC). Respondents include data professionals and members of these companies' management boards. This focus is justified because data professionals and members of the management board specifically supervisors and managers within Global Business Services (GBS) companies with Malaysia Digital Status possess the necessary technical expertise and strategic oversight to effectively implement and utilize Big Data technologies. Moreover, the GBS companies are chosen as they are likely to implement Big Data adoption (PwC, 2021) and participate MDEC's digital transformation effort includes Big Data Analytics.

3.3.6 Questionnaire Design

The questionnaires were intended for individuals in the companies that have a relationship with Big Data adoption agenda such as C-Suite Level, middle managers and data professionals (Data Analyst, Data Engineering, Data Administrator etc.). The first step in deciding who and what to analyze is to define the unit of analysis. It is important to understand that unit of analysis is not the same as unit of observation

(Trochim, 2000). According to Trochim (2000), unit of analysis can be Individuals, organizations, artifacts (books, pictures, newspapers), geographical units, or social interactions can all serve as units of analysis. Creswell (2012) also said that, in social science research, the unit of analysis is a group, individual, or organization. The selection of these respondents as data sources was based on Philips (1981) assertion that high-ranking informants provide more credible information than their lower-ranking colleagues.

Zikmund (2003) stated that, in designing the questionnaire, basic criteria of relevance and accuracy should be considered. In this study, the questionnaire (see Appendix 1) consisted of forty-two questions which consist of two parts. The details of each part are as follows:

a) Part I: Question 1-7 regarding background information of respondents.
b) Part II: Question 8-42 was designed to examine the independent variable, the dependent variable and the moderator.

3.3.7 Data Measurement Scale

Empirical studies have supported the use of a five-point Likert scale for each concept, emphasizing its usefulness in balancing respondent cognitive burden and data accuracy, particularly in technology adoption studies (J. Hair et al., 2017 ; Taherdoost, 2021). Furthermore, the five-point Likert scale corresponds to previous Big Data adoption research, ensuring consistency and comparability with existing findings (Al-Rahmi et al., 2019; Liao et al., 2023; Shabbir & Gardezi, 2020). According to Sekaran and Bougie (2009), the Likert scale accurately reflects respondents' levels of agreement or disagreement, and Singh (2021) found that it produces greater reliability coefficients for complex constructs in digital adoption, reducing cognitive burden for respondents. The applicability of the Likert scale has been widely demonstrated in the business and social scientific literature (Garland, 1991), as it increases answer variance and leads to more reliable assessments.

3.3.8 Data Measurement Error

The difference between observed and actual values of variables is known as measurement error, and it is frequently caused by mistakes in the data gathering process (J. F. Hair et al., 2019). These errors are classed into two types: random errors, which occur unexpectedly and undermine data reliability, and systematic errors, which incorporate bias into the results, potentially leading to inaccurate conclusions (W. J. Creswell & Creswell, 2018). Random errors were mitigated by conducting a pilot test, which facilitated the identification of inconsistencies or ambiguities in the questionnaire that could have caused variability in responses. Systematic errors, such as common method bias, were reduced by using approaches such as, Harman's single-factor test, and variance inflation factor (VIF) analysis, as proposed by (Philip M Podasakoff et al., 2003).

Pilot Test

A pilot test was undertaken to improve the questionnaire's clarity and consistency, hence reducing random errors (Saunders et al., 2015). By optimizing the survey instrument according to pilot test input, the study minimized random discrepancies in participants' comprehension and responses, hence improving the overall dependability of the data collection process.

Common Method Bias

Harman's Single-Factor Test

Harman's single-factor test was conducted to identify common method bias. This method assesses if a singular factor explains the predominant variance, suggesting potential bias stemming from the measurement technique (Philip M Podasakoff et al., 2003). This investigation verified that common technique bias was not a substantial concern.

Variance Inflation Factor (VIF) Analysis for Full Collinearity Test

VIF was employed to evaluate multicollinearity, which can inflate the relationships between variables and contribute to systematic bias. The results showed that all VIF values were below the recommended threshold, indicating no issues with collinearity (J. F. Hair et al., 2019).

Survey Bias – Non response bias

Additionally, a test of survey bias, particularly non-response bias, was performed to ensure that early and late respondents did not exhibit significant differences in the responses, which could distort the results (F. J. Hair et al., 2014). Multi-Group Analysis (MGA) was used to determine whether early and late respondents had any systematic differences, ensuring that non-response bias was not an issue (Sarstedt et al., 2011; J. F. Hair et al., 2014). In this investigation, no substantial bias was identified between the two groups, as evidenced by the MGA results, assuring the data's dependability. These metrics, combined with the SEM-based assessment of construct validity and model fit (J. F. Hair, Ringle, et al., 2013; J. F. Hair & Brunsveld, 2019), reduced the impact of measurement error on the results.

3.4 Population and Sampling

3.4.1 Population and Sample Size

The study's population includes 428 active Global Business Services (GBS) companies with Malaysia Digital Status, as established by the Malaysia Digital Economy Corporation (MDEC, 2022c). These companies were chosen because of their involvement in MDEC's digital transformation efforts (PwC, 2021). These companies' target responders include data professionals, as well as senior and intermediate managers participating in Big Data strategies. This focus guarantees that both technical and strategic views are included when analyzing Big Data adoption and its influence on organizational performance.

To create a trustworthy and generalizable sample, this study used Krejcie and Morgan's (1970) table to calculate the minimal sample size. To obtain statistically meaningful results from a population of 428 companies, a sample of 201 respondents is required. To account for probable non-responses and ensure robust data analysis, the G*Power software was used to calculate the required sample size based on the desired power level, effect size, and alpha level Cohen (1988) . G*Power calculations indicated that a sample size of 129 would be sufficient to get significant results with a 95% confidence level and a 5% margin of error. Given this, the researcher chose to distribute the survey to 201 of the 428 GBS companies.

With the lower response rates characteristic of management and technology studies in Malaysian organisations, which vary between 25% and 35% (Vafaei-Zadeh et al., 2020; Vafaei-Zadeh et al., 2020), a larger dissemination strategy was implemented. To ensure a minimum of two responses per company, the questionnaires were distributed to 2-5 individuals per company across both phases. This approach increased the likelihood of obtaining adequate responses, considering varied roles and availability within each organization.Between June 2021 and March 2024, 700 questionnaires were delivered to target respondents in these 201 companies. To address any disruptions caused by the COVID-19 pandemic, an extended data collection period was implemented, along with follow-up reminders by email, LinkedIn, WhatsApp, and phone calls.

Finally, a sample of 272 respondents was obtained, which exceeded the minimum need based on both Krejcie and Morgan's (1970) table and G*Power calculations. This greater sample size improves the study's reliability and validity, guaranteeing that the results may be applied to a larger population of GBS organizations.

3.4.2 Sampling Technique

The sampling technique used in this study changed in response to obstacles encountered during data gathering. Initially, simple random sampling method was used to ensure that each company in the population had an equal chance of being selected. Each GBS company was issued a unique identifier, and the initial responders were chosen at random using a number generator. This strategy was intended to decrease bias and give a representative subset of the population (Sekaran, 2003).

However, due to low response rate and the disruptions caused by the COVID-19 pandemic, the study switched to a convenience sampling method in the second phase. Convenience sampling selects respondents who are readily available and willing to participate (Sekaran & Bougie, 2016). This change was required to meet the minimal sample size and keep the study on track despite external constraints.

To summarize the techniques applied to the study, a combination of random sampling (in the first phase) and convenience sampling (in the second phase), yielding a total sample size of 272 participants. The use of convenience sampling was carefully handled to eliminate potential bias, and follow-up procedures, such as Whatsapp and email reminders, and occasionally contacting a company representative to encourage participation from other team members, to assure a diverse and representative sample of respondents. This integrated approach allowed the study to achieve its aims and deliver credible results.

The Krejcie and Morgan (1970) is the common approach for determining sample size because it gives a practical way to calculate the sample size required for a given population size. This strategy is very important for ensuring that the sample size is neither too small nor too large, preserving the study's validity and reliability (Krejcie & Morgan, 1970). By taking this strategy, researcher can securely choose a sample size that accurately represents the population, increasing the overall credibility of the research findings. Based on Krejcie & Morgan (1970), for a population of 428 the sample respondent of 201 is sufficient to achieve reliable and generalizable results.

However, there is another software tool that is viable for identifying sample size that is G*Power (Faul et al., 2013). G*Power enables researchers to adjust the sample size computations to the specific criteria, such as effect size, alpha level, and statistical power. This allows for a more precise and tailored estimation of the required sample size. G*Power provides a wide range of statistical tests, making it adaptable to varied study methods and hypotheses Furthermore, it gives extensive output that helps researchers understand the impact of their selections on statistical power and potential errors, hence increasing the reliability and validity of their research findings (Erdfelder et al., 2009).

A sample size of 129 is sufficient for conducting the statistical analysis of multiple linear regression in this study, as indicated in Figure 3.3. Additionally, the study refers to Cohen (1988), who suggests using a value of 0.95 for determining the effects. The minimum required sample size for achieving a statistically significant result would be 129, assuming a 95% confidence level and a 5% margin of error. This calculation was performed using G*Power 3.1.9.7. The sample size N was determined based on the desired power level (1- β), the predetermined significance level α, and the probability 1–β, in order to ascertain the effect size of the population. To calculate the sample size, a priori power analysis was performed using the G*Power 3.1.9.7 program (Leoniak & Cwalina, 2019). The sample size in this investigation was determined using the standards established by Cohen (1988). The components of the analysis include the effect size (f^2=0.15), the significance alpha level (α=0.05), the desired statistical power (1-β=0.95), and four predictors (data quality management, data security, ease of use and top management support).

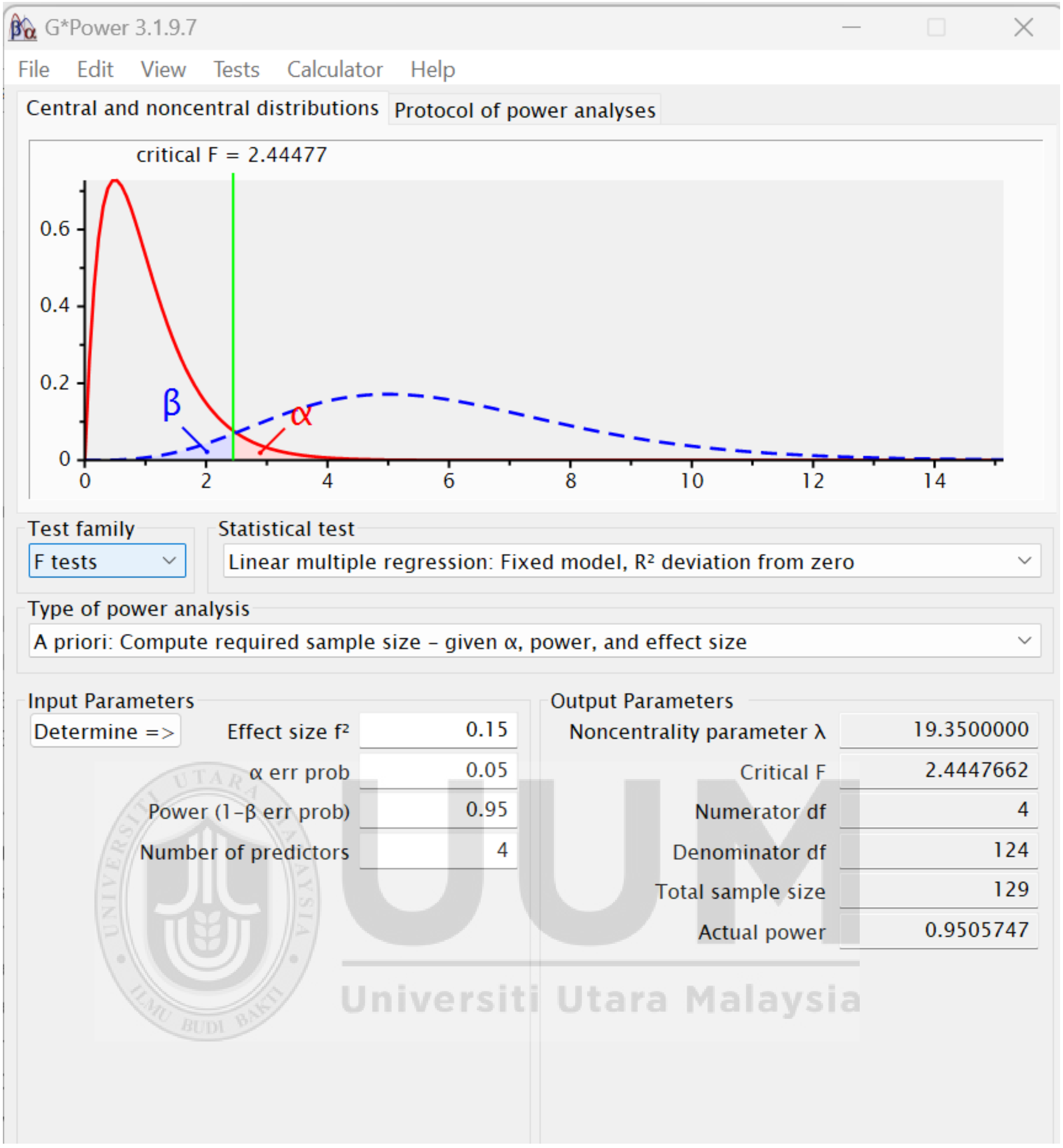

Figure 3.3
*G*Power Test Result*
Source: Adopted from Faul et al. (2013)

The final sample size of 272 respondents exceeded the minimum requirements set by both Krejcie and Morgan (201) and G*Power (129), ensuring robust statistical validity for the study. Additionally, Hair et al. (2019) suggest that, for PLS-SEM analysis, a sample size should be ten times the maximum number of structural paths directed toward any construct in the model, implying a minimum of 90 respondents. The larger sample size of 272 respondents provided a solid basis for a more comprehensive analysis using PLS-SEM.

The final response rate of 39% demonstrates the effectiveness of the multi-phase data collection strategy, with proactive follow-up measures to maximize participation. This rigorous sampling approach ensured that the study findings were statistically accurate and applicable to the larger GBS company population.

3.4.3 Justification for Sample Size

For this study, determining a suitable sample size was critical to ensuring the findings' reliability, validity, and generalizability. According to Krejcie and Morgan's (1970) recommendations, for a population of 428, a minimum sample size of 201 respondents is required to generate statistically significant results. Furthermore, a G*Power analysis was performed to revise this estimate, indicating that a sample size of 129 would be enough at a 95% confidence level and a 5% margin of error. Given these needs, a larger sample size was chosen to account for anticipated non-responses, data discrepancies, and response variability, hence boosting the study's predictive power.

A total of 700 questionnaires were sent across two periods to ensure that both Krejcie and Morgan's and G*Power's minimum requirements were met while also maximizing the reliability and robustness of the study results. This approach yielded 272 valid responses, exceeding the initial sample size projections, increasing the study's ability to offer statistically reliable and generalizable findings for Malaysia's GBS sector.

The selected sample size also considers the possibility of Type I and Type II mistakes.

A small sample size could compromise the population's true representativeness and raise the chance of a Type I error, which involves incorrectly rejecting a valid hypothesis (Sekaran & Bougie, 2016). In contrast, an excessively large sample size may increase the probability of a Type II error, in which an incorrect hypothesis is accepted (Sekaran & Bougie, 2016). The appropriate sample size is critical in any research since a small sample size may risk the real representativeness of the study's population (Cheah et al., 2018). To strike the right balance and provide accurate results, a strong sampling technique is essential to establish the best sample size for the study population (Trafimow & Earp, 2017)

By using a final sample size of 272, this study ensures that the findings are not only statistically sound but also generalizable to the larger population of Malaysian Digital Status GBS companies, meeting the rigorous standards of methodological reliability and representativeness in Big Data adoption research.

3.5 Data Collection Procedure

To fulfil the study's objectives, a systematic data collection procedure was used, with an emphasis on obtaining insights from individuals involved in management and data operations at Global Business Services (GBS) businesses. Given the changing nature of the digital economy and the importance of Malaysia Digital Status organizations in promoting technological adoption, it was necessary to collect information from relevant professionals who could provide educated viewpoints on the research variables. The data collection method was developed to maximize participation while addressing potential problems, such as low response rates and limits imposed by external conditions, such as the COVID-19 pandemic. This section describes the precise methods and methodologies utilized to collect the essential data.

The data collection for this study focused on data professionals and the management board (supervisors and managers) of Global Business Services (GBS) businesses that have Malaysia Digital Status, as determined by the Malaysia Digital Economy Corporation (MDEC). Initially, simple random sampling was used. However, due to difficulties in getting responses, convenience sampling was eventually adopted. This adjustment sought to collect information more effectively during the COVID-19 epidemic, allowing research to continue despite the limitations of movement restrictions.

The survey included 428 GBS companies listed on the MDEC website. The survey data was collected from 272 respondents (estimated two people from their organizations). This sample size exceeded Krejcie and Morgan's (1970) suggestion of a minimum of 201 for populations of this size. Furthermore, the G*Power tool (2013) 013) showed that a sample of 129 would be sufficient for the requested statistical analysis, implying that the obtained sample size was enough for the study.

A self-administered online questionnaire delivered via Google Forms was the primary data gathering instrument. To increase response rate and involvement, the message was distributed via email, WhatsApp, LinkedIn, and other social media sites. This method was chosen for its cost-effectiveness, ease of administration, and ability to protect respondents' confidentiality (Noor, 2020; Vafaei-Zadeh et al., 2019). However, the use of online surveys has disadvantages, most notably a reduced response rate, which was mitigated by follow-up reminders (Shiyab et al., 2023).

The questionnaire was designed with a five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5). This scale was chosen for its capacity to capture respondents' attitudes and views of the study variables, hence increasing data validity and reliability (Coombes et al., 2021).

The data collection method was divided into two sections. The first phase, which lasted from June 2021 to September 2023, used simple random sampling. However, due to the poor response rate, the researcher switched to convenience sampling for the second phase, which took place from December 2023 to March 2024. Despite the hurdles, particularly during the COVID-19 epidemic and different Movement Control Orders (MCOs), the ultimate response rate was 39%, with all surveys completed and ready for processing.

Convenience sampling was regarded beneficial after several years of low response rates, as it allowed researchers to select individuals who were easily available, ensuring data collection could continue despite limitations (Sekaran & Bougie, 2013). Phone calls, Whatsapp, and email reminders were used to complement this technique, and they have been found to effectively enhance response rates (Shiyab et al., 2023).

The researcher used a variety of tactics to manage non-responses, including email, WhatsApp, and LinkedIn follow-ups. In certain circumstances, the researcher contacted a company representative to urge the participation of other team members.

Furthermore, respondents were informed of the confidentiality and anonymity of their comments, which alleviated concerns about privacy.

To ensure data accuracy, all fields in the Google Forms were marked as required, forbidding incomplete input. As a result, the dataset contained no missing values, and all returned questionnaires were completely useable for analysis. This meticulous approach to data management resulted in a complete and reliable dataset, assuring the validity of the study findings.

The study followed stringent ethical norms. Each questionnaire was accompanied by a cover letter that explained the study's goal and ensured the respondents' confidentiality and anonymity. Participants were notified, in accordance with ethical norms, that their data would only be used for academic reasons, and that the names of companies and people would not be released.

The combination of these procedures meant that enough data was obtained to achieve the study's objectives, despite the constraints created by the COVID-19 epidemic. This study's data gathering process was robust and adaptive, with both basic random and convenience sampling strategies used to capture a full dataset from Malaysian GBS companies. The use of online questionnaires, together with follow-up reminders and ethical concerns, helped achieve a sufficient response rate while protecting the data's confidentiality and integrity. These methodologies, combined with recognized research practices (Krejcie & Morgan, 1970; Sekaran & Bougie, 2016), ensured that the data acquired was reliable and suitable for further analysis.

3.6 Operational Variables

In this section, the study's major constructs are operationalized to determine their impact on organizational performance in the context of Big Data adoption. These components include data quality management, data security, ease of use, top management support, training, and organizational performance. A five-point Likert scale is used to assess respondents' opinions and attitudes towards each variable. This scale is well-known for its ease and effectiveness in capturing complex data while reducing cognitive strain on respondents (Dillman et al., 2024; Coombes et al., 2021).

The adoption of a five-point Likert scale for each concept (data quality management, data security, ease of use, top management support, training, and organizational performance) necessitates a strong rationale. Likert scales are extensively used in organizational research to collect subjective data on perceptions, attitudes, and behavioural intentions. A five-point scale is widely regarded for its ease and reliability in decreasing respondents' cognitive load while providing adequate granularity for analysis (Dillman et al., 2024). Furthermore, studies suggest that the five-point scale balances answer accuracy with ease of understanding, hence boosting data quality (Coombes et al., 2021).

3.6.1 Data Quality Management

Data quality is a complex concept that must be paired with other factors to adequately explain its dimensions (Onyeabor & Ta'a, 2018). For example, data quality management can be grouped by correctness, completeness, and consistency. Each component was operationalized using several indicators to capture the overall quality of data management inside the company.

In the context of organizational performance, understanding data quality requires analyzing its accuracy, completeness, consistency, and timeliness (Wahyudi et al., 2018). Cronbach's alpha for similar items implemented in several studies ranges from 0.90-0.93 (Shamim et al., 2019; Dias et al., 2021). Table 3.1 presents the adopted items used to measure data quality management.

Table 3.1
Survey Items to Measure Data Quality Management

Variables	**Item Code**	**Survey Items**	**Cronbach Alpha**	**Source**
Data Quality Management	DM1	The organization recognized the complexity of data quality due its large volume, velocity, and variety.	0.90	(Dias et al., 2021; Shamim et al., 2019)
	DM2	The organization has a clearly defined strategy for Data Quality Management.		
	DM3	There is a clear ownership of data within the organization.		
	DM4	There is a complete reference model for Data Quality and its Management in Big Data.		
	DM5	There is a centralized data warehouse to consolidate data from various sources.		
	DM6	The organization uses right assessment scheme and quality measurement to address Big Data Quality issues.		
	DM7	The organization established Data Governance to achieve common goals to address data quality across functions.		

3.6.2 Data Security

Data security threats happen when data is extensively shared and easily accessible. Compliance issues with an emphasis on what rules and regulations should be in place to limit the collecting and storage of personal information should be investigated (Salleh & Janczewski, 2019). Data security was analyzed using factors such as confidentiality, integrity, and availability. These variables assess how successfully a business secures its data from breaches and unauthorized access while adhering to data protection standards.

Cronbach's alpha for similar items implemented in several studies ranges from 0.92 (Shamim et al., 2019; Dias et al., 2021; Asiri et al., 2024). Table 3.2 presents the adopted items used to measure data security.

Table 3.2
Survey Items to Measure Data Security

Variables	**Item Code**	**Survey Items**	**Cronbach Alpha**	**Source**
Data Security	DS1	The organization is aware of the risk of legal repercussions and reputational damage if a security breach of corporate Big Data occurs.	0.92	(Asiri et al., 2024)
	DS2	The complexity in various regulatory and compliance processes hinders the exploration of data insights.		
	DS3	The organization implemented security awareness programs to foster a data security protection culture.		
	DS4	The organization established security policies and controls guidelines to manage data protection culture.		
	DS5	The organization possess a strong authentication mechanism to manage access control to the corporate database.		
Data Security	DS6	The organization is willing to invest in a highly secured data detection tool to prevent the breach of corporate data.	0.92	(Asiri et al., 2024)
	DS7	The organization embarked on the ethical code of conduct as ethical checks when conducting Big Data projects.		

3.6.3 Ease of Use

Ease of use was defined as an individual's belief that specific technology will need no effort (Davis, 1989). Similarly, perceived ease of use was defined as a user's ability to handle the system and get it to perform what is necessary, with less mental effort required to engage with the system, and the system's ease of use (Lai et al., 2018; Al-Rahmi et al., 2019; Ujang et al., 2023). The ease of use of Big Data tools and technologies was assessed by quantifying their ease, usability, and learnability (F. D. Davis, 1989). This construct measures the ease with which users adopt and integrate Big Data solutions into their processes. Cronbach's alpha for similar items implemented in several studies ranges from 0.92 (Lai et al., 2018). Table 3.3 presents the adopted items used to measure ease of use.

Table 3.3
Survey Items to Measure Ease of Use

Variables	**Item Code**	**Survey Items**	**Cronbach Alpha**	**Source**
Ease of Use	EOU2	Big Data Analytics would require fewer steps to discover insights.	0.92	(Lai et al., 2018)
	EOU3	Big Data Analytics would enable me to accomplish tasks quickly.		
	EOU4	Big Data Analytics would require advance skills to analyze.		
	EOU5	Big Data Analytics would improve my job performance.		
	EOU6	Big Data Analytics would enhance the capability to complete work effectively.		
	EOU7	I find Big Data Analytics useful for my job.		

3.6.4 Top Management Support

Top management support is essential for the successful use of Big Data technology and increased organizational performance. John P. Kotter, a well-known academic on this issue, emphasizes the need of strong leadership and dedication from top management in driving change and boosting performance (Kotter, 1996). Top management support for Big Data projects was examined using variables such as commitment, resource allocation, and leadership's strategic direction (Lai et al., 2018). This evaluates how involved and supportive senior management is in the adoption and implementation of Big Data initiatives.

Cronbach's alpha for similar items implemented in several studies ranges from 0.87 to 0.94 (Lai et al., 2018; Ghaleb et al., 2021; Thanabalan et al., 2024). Table 3.4 presents the adopted items used to measure top management support.

Table 3.4
Survey Items to Measure Top Management Support

Variables	**Item Code**	**Survey Items**	**Cronbach Alpha**	**Source**
Top Management Support	TM1	The leadership team demonstrated good knowledge of Big Data projects.	0.87-0.94	(Lai et al., 2018; Ghaleb et al., 2021; Thanabalan et al., 2024)
	TM2	A managerial (c-level) role (e.g. Chief Data Officer) is created to manage the response of Big Data Adoption.		
	TM3	The leadership team is united across the divisions to support Big Data projects.		
	TM4	The Big Data Analytics Project is included in the organization's transformation play.		
	TM5	The leadership team is clear about what type of training needs to be provided to increase the skills in Big Data.		
	TM6	The leadership team has a good career development plan for high-skilled employees to pursue Big Data projects.		
	TM7	The leadership team connects high-skilled employees with business leader to make a difference with Big Data Projects.		

3.6.5 Training

Continuous learning allows individuals to eagerly share information with others in the workplace. The healthcare organization demands formal training for all employees in order to sustain the company's growth. Continuous training allows people to learn new abilities required to execute their professions (Ghaleb et al., 2021). According to Hanci-Donmez & Karacay (2019) and Md Amin (2022) an organization with higher-quality human resources, such as greater education or training, will have a larger ability to innovate. Training was operationalized in terms of skill enhancement, continuous learning, and resource development (Ghaleb et al., 2021). This construct assesses the availability and efficacy of training programs that provide employees with the skills required to properly use Big Data technologies. Cronbach's alpha for similar items implemented in several studies ranges 0.86 (Ghaleb et al., 2021). Table 3.5 presents the adopted items used to measure training.

Table 3.5
Survey Items to Measure Training

Variables	Item Code	Survey Items	Cronbach Alpha	Source
Training	TNG1	There is an interest from all levels to understand the value of Big Data Analytics	0.86	(Ghaleb et al., 2021)
	TNG2	The organization is willing to invest in trainings to upskill the resources		
	TNG4	Training would increase my skills in Big Data Analytics		
	TNG5	Training would increase the usability of Big Data Analytics		
	TNG6	I am able to put into practice what I've learned about Big Data Analytics		

3.6.6 Organizational Performance

Organizational performance refers to how well an organization meets its goals and objectives, which include financial performance, operational efficiency, market share, and other key performance indicators. It is a term that evaluates an organization’s success in providing value to its stakeholders. According to previous studies, implementing Big Data Analytics can considerably improve organizational performance by enhancing decision-making processes, increasing operational efficiency, and encouraging innovation (Sekli & De La Vega, 2021; Nasrollahi et al., 2021; Lutfi et al., 2022; Asiri et al., 2024). Nasrollahi et al. (2021) discovered that Big Data adoption improves both operational and economic performance in SMEs, emphasizing the revolutionary power of Big Data technologies. Similarly, Asiri et al. (2024) shown that Big Data Analytics improves organizational performance through better knowledge management techniques. Organizational performance was assessed through operational efficiency, competitive advantage, and market value (Nasrollahi et al., 2021). Operational efficiency investigates how successfully a business maximizes its resources, whereas innovation capability assesses the ability to develop new products or services. Operational efficiency measures how well a company optimizes its operations and cuts costs, whereas competitive advantage measures how Big Data usage improves the organization's market position over competitors. Market value evaluates the financial gains and sustainability obtained by utilizing Big Data technology, thereby enhancing shareholder value and long-term performance (Nasrollahi et al., 2021; Sekli & De La Vega, 2021) Asiri et al., 2024). Cronbach’s alpha for similar items implemented in several studies ranges 0.82 (Asiri et al., 2024). Table 3.6 presents the adopted items used to measure organizational performance.

Table 3.6
Survey Items to Measure Organizational Performance

Variables	Item Code	Survey Items	Cronbach Alpha	Source
Organizational Performance	OP1	The organization performance has improved its operational landscape and shown interest in Big Data Analytics.	0.82	(Asiri et al., 2024)
	OP2	The organization was able to introduce new innovations with the adoption of Big Data Analytics.		
	OP3	Big Data Analytics capabilities accelerate and improve the decision-making process.		
	OP4	Big Data Analytics adoption increased ROI (Return on Investment) for the organization.		
	OP5	Big Data Analytics adoption accelerated the cost reduction / cost avoidance for the organization.		
	OP6	Big Data Analytics adoption improved customer experience and retention through analytical capabilities.		
	OP7	With accurate predictions through Big Data Analytics, the organization has gained the competitive advantage.		

3.7 Data Analysis Method

This study used quantitative data analysis techniques as the method for data analysis. This analysis involved the analysis of numerical data. The methods of data analysis were chosen based on the research objectives and the variable characteristics (Lammers & Babbie, 2005).

3.7.1 Type of Statistical Analysis

In general, there are two common theories employed in statistical research: Correlation statistical analysis theory and comparison statistical analysis theory (Tabachnick & Fidell, 2018). Some features of classification tests are shared by both statistical theories, including the approaches, both parametric and non-parametric, that depend on the general presumptions of the relevant statistical tests (Field, 2005). The terms univariate, bivariate, and multivariate statistical tests are based on particular assumptions for conducting these tests, when applying the correlational and comparative statistical analysis theories (Pallant, 2016).

Analyzing a single variable at a time is known as univariate analysis (Pallant, 2016). An analysis with just one variable (e.g., a comparison study between one variable and several groups). A univariate statistical analysis is a statistical study that solely examines one variable, such as comparing one variable to other groups. Bivariate analysis, as used by Field (2005) and Pallant (2016), is the process of analyzing two variables simultaneously. But only in relation to relationship analysis, like correlation analysis, does this analysis exist. Multivariate analysis, as defined by J. F. Hair, (2021), Johnson and Wichern (2007), Hair et al. (2013) and Tabachnick and Fidell (2018), entails analyzing multiple variables simultaneously.

Smart PLS is a statistical tool developed by a group of German academic software developers (Ringle et al., 2014). Researchers investigating the theories frequently utilize this statistical program, which does SEM analysis using the Ordinary Least Square estimation approaches (Hair et al., 2012; Hair et al., 2013).

3.7.2 Data Screening and Preliminary Analysis

Data screening is a process that ensures the data is usable, reliable, and valid. Initial data screening enables researchers to identify any destruction in data analysis (Hair et al., 2009). After data coding and entry, preliminary data analyzes were conducted which are missing value analysis and assessment of outliers (Hair et al., 2012).

3.7.3 Testing of Survey Bias

This study used two fundamental methodologies to assess potential survey biases: the Non-Response Bias Test and the Common Method Bias Test. Non-response bias might comprise the validity of research findings when there are systematic variations between early and late respondents (F. J. Hair et al., 2014). To address this, a Multi-Group Analysis (MGA) was performed in SmartPLS 4 utilizing the Bootstrapping approach, allowing for a comparison of structural correlations between early and late respondents (J. Hair et al., 2017). The consistency of path coefficients across these groups suggested that non-response bias was unlikely to influence the study's findings.

Common method bias (CMB), a common issue in survey-based research, occurs when measurement errors cause systematic variance, possibly magnifying correlations across constructs and weakening the validity of the results (Philip M Podasakoff et al., 2003). To address this, two approaches were used. First, the Full Collinearity Test was performed in SmartPLS4 utilizing Variance Inflation Factor (VIF) values that were less than 3.3, as per Kock's (2015) requirement, indicating that there is no significant CMB. Furthermore, Harman's Single-Factor Test was utilized to identify any strong common variance. These bias tests validated the survey data's robustness and reliability, ensuring that the results were free of the common biases associated with survey responses.

3.7.4 Missing Value Analysis

Missing value analysis is an important step in ensuring the integrity and reliability of research data, as missing values can introduce biases and alter results (Kwak and Kim 2017). Missing values can occur for a variety of reasons, including respondents skipping certain questions, data entry errors, or discrepancies in the survey design. These missing values can cause substantial difficulties, such as a loss of statistical power, biased estimations, and a decrease in the validity of the conclusions.

Missing data were proactively prevented in this study by requiring mandatory responses to all survey questions via the Google Forms platform. This setting ensured that respondents could not submit the survey until all relevant fields were completed. By requiring this obligatory setting, the problem of missing data was effectively eliminated, reducing the possibility of measurement error (J. F. Hair et al., 2012).

Following data collection, a rigorous data screening was performed to ensure that there were no empty cells or incomplete responses in the dataset. Existing literature supports this strategy, emphasizing the need of resolving missing values early in the data collecting phase to improve data quality and reduce random mistakes (Tabachnick & Fidell, 2018). As a result, the study could proceed without the use of imputation techniques because all responses were complete.

3.7.5 Assessment of Outliers

Outliers is an observation of inconsistence with other data (Barnett & Lewis, 1995). Outliers can significantly distort regression coefficient estimates, resulting in untrustworthy results (Kwak & Kim, 2017). The outliers may occur because respondent have extreme opinions in their answers (Hair et al., 2014). Outliers can be the extreme values that can distort the results if not properly handled. Structural Equation Modeling (SEM) often includes methods for identifying and managing outliers to ensure that they do not affect the validity of the analysis (J. F. Hair, Ringle, et al., 2013).

3.7.6 Structural Equation modeling (SEM)

Structural Equation modeling (SEM) is the most appropriate method to apply to investigate the causal and effect link between several independent and dependent variables (Byrne, 2012; Hair et al., 2012; Fan et al., 2016). Structural Equation modeling (SEM) was employed to explore causal relationships and effects between multiple independent and dependent variables, with a focus on understanding how various factors impact Big Data adoption and organizational performance. Among the SEM approaches, PLS-SEM (Partial Least Squares SEM) was selected for several key reasons. Unlike Covariance-Based SEM (CB-SEM), which is more suited for theory confirmation, PLS-SEM is designed for theory development and is highly effective in predictive analysis. This aligns well with the exploratory nature of this research, which seeks to evaluate how different constructs like data quality management, data security, ease of use, and top management support, as well as moderating factors like training, influence organizational outcomes.

PLS-SEM is particularly advantageous for handling complex, multidimensional models with numerous constructs and indicators, as seen in this study. According to (J. F. Hair, 2021), PLS-SEM is particularly ideal for predictive analysis in complex, multidimensional contexts because it allows for out-of-sample predictive evaluation.

This makes it a robust tool for studies that intend to study dynamic interactions across components. It allows researchers to simultaneously test relationships among independent, mediating, and dependent variables, accommodating both reflective and formative measurements (J. Hair et al., 2017). Moreover, PLS-SEM is robust in handling small sample sizes and doesn't require the data to meet normal distribution assumptions, making it more flexible than traditional CB-SEM approaches (Byrne, 2012; J. F. Hair, Hult, et al., 2013; Zhang et al., 2021).

This is especially beneficial for studies like this one, where there are higher-order constructs, such as operational efficiency and market value, and a multidimensional path model. Additionally, PLS-SEM allows the integration of both first-order and second-order constructs, offering nuanced insights into how individual dimensions of the constructs affect the overall model. J. F. Hair (2021) emphasize the benefit of PLS-SEM in accepting higher-order components, such as those encountered in complex, multidimensional research, which improves the model's ability to capture intricate interactions between factors determining organizational results. For instance, the higher-order constructs in this study, such as organizational performance, are evaluated through dimensions like operational efficiency, competitive advantage, and market value, which offer a more comprehensive analysis of the relationships between the independent variables and the dependent outcomes (J. F. Hair & Sarstedt, 2019). This approach ensures a more sophisticated model, thereby enhancing the predictive power and accuracy of the findings.

In summary, PLS-SEM's flexibility, predictive focus, and ability to handle complex models made it the most suitable method for this study, allowing for comprehensive exploration of the multifaceted relationships influencing Big Data adoption and its impact on organizational performance.

3.7.7 Descriptive Statistics

Descriptive statistics is a simple quantitative summary of the data set that was obtained. It shows the results of mean, standard deviation, minimum and maximum. Maximum is defined as the largest value, while minimum is defined as the smallest value in the data set. Means measures the center of a batch of numbers. Standard deviation measures the spread of data.

3.8 Pre and Pilot Test

This study involved refining the questionnaire via a pre-test with expert feedback to guarantee the survey instrument was user-friendly, precise, and concise. The expert panel comprised two academic experts and two industry experts. The academic specialists were affiliated with Universiti Utara Malaysia and Universiti Malaysia Pahang, whereas the industry expert held a managerial position at an Malaysia Digital Status companies.

Their constructive criticism concentrated on several critical aspects: enhancing the user experience of the inquiries, ensuring the appropriate vocabulary was employed, and minimizing the word count in each line to guarantee brevity and precision. Each expert meticulously examined the questionnaire's phrasing and organization to guarantee precision and consistency with the desired objectives.

The academic experts assessed the theoretical robustness and suitability of the measuring items to ensure content validity, while the industry expert contributed practical perspectives on the questionnaire’s relevance and applicability in actual business environments. The phrasing and sequence of the questions were updated according to their recommendations, and superfluous or unclear material were either amended or removed. The expert assessments were essential in improving the measurement instrument's quality and content validity, guaranteeing that the questions were both theoretically robust and practically applicable for the respondents.

Next, a pilot test is conducted before the actual survey to improve the survey’s consistency and reliability. Additionally, it can help researchers find previously unknown confounding variables. Pilot research ensures that the questionnaire content, usability, and explanation are extensively tested before performing a comprehensive survey. Data was collected by a systematic survey using an updated questionnaire designed (Srinivasan & Lohith, 2017).

Furthermore, this pilot test aids in identifying potential obstacles and helps the researcher to improve the instrument before beginning the actual research. Validity refers to how accurately an instrument measures what it is designed to examine, whereas reliability refers to how error-free an instrument is and how consistently stable its results are across different scale components. Braun et al. (2021) conducted a pilot study that implemented the pilot feasibility test recommendations.

The pilot test is essential for ensuring the questionnaire's usefulness and alignment with the study's objectives. It identifies potential errors, tests the instrument's reliability and validity, and refines the survey prior to full implementation (Sekaran & Bougie, 2016). The study conducted a pilot test with 40 respondents from Malaysian Digital Status companies. The pilot test lasted one month and was conducted online using email and WhatsApp. The sample size of 40 responders is comparable with literature recommendations, which state that pilot studies typically have 25 to 100 participants (Boris Blumberg et al., 2014).

The primary objective of the pilot study was to determine the consistency and reliability of the questionnaire. The survey was created using previously validated scales; however it was important to guarantee that the questions were understood by the target demographic in Malaysia. Respondents were asked for input on the questions' clarity, language, and length, as well as the overall usability of the online survey instrument (Cooper, D. R., & Schindler, 2011). This feedback enabled the researcher to fine-tune the questionnaire, ensuring that any ambiguities were resolved and that the instrument was culturally and contextually acceptable for the study environment (Chockalingam & Ramayah, 2013).

The survey items' reliability was assessed using Cronbach's alpha, a measure of internal consistency. A Cronbach's alpha score more than 0.70 was regarded appropriate for each construct as illustrated in Table 3.7, including data quality management, data security, ease of use, top management support, and training (J. F. Hair et al., 2011). The pilot test findings revealed that all constructs met the reliability criterion, indicating that the instrument was suitable for continuing use in the main study.

Table 3.7
Result of the Pilot Study

No	Construct	Cronbach's alpha
1	Data Quality Management	0.893
2	Data Security	0.862
3	Ease of Use	0.813
4	Top Management Support	0.935
5	Training	0.803
6	Organizational Performance	0.892

This approach ensured that the questionnaire was customized for data collection, reducing the possibility of measuring errors during the survey. By modifying the instrument during the pilot test, the study was able to improve the research's reliability and validity, providing accurate and meaningful results for the main survey.

3.9 Reliability and Validity Test

The validity test determines how well the instruments used in a study measure what they are designed to describe or assess. The primary goal of assessing validity is to determine the suitability of the approach, instrument, and study procedure (Hair, et al., 2013; Sekaran & Bougie, 2016 ; J. F. Hair, 2021). Scholars have identified various approaches for establishing validity; however, construct validity, content validity, predictive validity, concurrent validity, and face validity are the most commonly used in many studies (Dr. Greener & Dr. Martelli, 2008; Vanderstoep & Johnston, 2022). Among these, construct validity is particularly critical for data analysis (Dr. Greener & Dr. Martelli, 2008).

The validity test in this study was intended to verify that the instruments employed accurately measured the target constructs. Several methodologies are used to measure validity, including construct validity, content validity, and predictive validity (J. F.

Hair, 2021; J. F. Hair, Ringle, et al., 2013; Sekaran & Bougie, 2016). Among these, construct validity is very important in assessing whether a test measures the theoretical concept it claims to (Dr. Greener & Dr. Martelli, 2008; Vanderstoep & Johnston, 2022). In this study, the instruments were rigorously tested to determine their suitability for evaluating dimensions linked to Big Data adoption and organizational performance.

Reliability, on the other hand, refers to the consistency and stability of measurements across repeated applications, ensuring that the instruments yield dependable results over time (J. F. Hair, 2021; Sekaran & Bougie, 2016). To assess reliability, Cronbach’s alpha was used to assess internal consistency. A Cronbach's alpha score of 0.70 or above is usually accepted, indicating that the items in a construct are closely related and measure the same underlying concept (J. F. Hair et al., 2012). For this study, each construct such as data quality management, data security, ease of use, top management support, and training had acceptable Cronbach's alpha values, supporting the instruments' reliability.

Furthermore, convergent and discriminant validity were tested to confirm that the constructs were internally consistent and distinct from one another. Convergent validity was tested using Average Variance Extracted (AVE), with values larger than 0.50 indicating significant convergence. Fornell & Larcker (1981) criteria were used to measure discriminant validity, which compares the square root of AVE to construct correlations. This ensured that each construct was sufficiently distinct from the others, confirming the suitability and correctness of the study's instruments.

3.10 Model's Predictive Relevance

The independent factors explain the R-squared of the dependent variable. As a result, the size of the R-squared for the dependent variables was used to assess the model's predictive potential. Furthermore, the approach of reusing samples was employed as developed by Geisser (1975) to confirm the predictive validity of the model. For this purpose, PLS was utilized since it is the optimal software for the sample reuse technique (Götz et al., 2010).

3.10.1 Coefficient of Determination (R^2)

The R-squared represents the amount of variance explained in the dependent variable by the independent variable. According to Cohen (1988), a R-squared value of 0.26 or more is regarded large, whereas 0.13 is considered moderate and 0.02 is considered weak. Furthermore, Chin W (1998) considered R-squared value that is equal or more than 0.67 significant, 0.33 moderate, and 0.19 weak.

3.10.2 Effect Size (F^2)

An effect size is a statistical metric that reflects the strength of a relationship. The strength of the moderating effects can be determined by comparing the primary effect model's coefficient of determination (R-squared value) to the overall model's R-squared value, which includes both independent latent variables and moderating factors (Memon et al., 2019; Pieters et al., 2022). Moderating effect sizes (f^2) of 0.02 are regarded small, 0.15 are moderate, and values more than 0.35 are considered high (Cohen, 1988).

3.10.3 Predictive Relevance (Q^2)

In the present study, the researcher utilized the Q^2 (Stone-Geisser) test to evaluate the predictive significance of the structural model utilizing the blindfolding technique in SmartPLS 4.0 This is recommended by J. F. Hair & Brunsveld, (2019). This strategy evaluates the model's predicted accuracy for the endogenous variable, in this instance Organizational Performance, by deliberately ignoring and forecasting portions of the data. A Q^2 value greater than zero implies the model has adequate predictive significance. This study found a Q^2 value of 0.45 for organizational performance, showing good predictive relevance. Chin W (1998) found that Q^2 values of 0.02, 0.15, and 0.35 suggest minor, medium, and large predictive importance, supporting the use of this approach in this study.

3.11 Summary

This chapter justifies the use of quantitative analysis to answer research questions and test hypotheses. It outlines the study's methodology. As previously indicated, this is a correlational study that employed appropriate statistical methods to analyze the causal relationships between the components under examination and assess the moderating impact.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter discusses the findings and conclusions drawn from the data analysis undertaken in this study. It starts with a review of the demographic distribution of respondents to offer context for the sample characteristics. The next analysis is to identify and mitigate any measurement errors that could affect the validity of the results such as missing value analysis, outlier detection, non-response bias and common method bias evaluations.

The following section is to evaluate the measurement model using Partial Least Squares-Structural Equation modeling (PLS-SEM) to confirm cconstruct reliability and validity through convergent and discriminant validity tests. In line with established SEM principles, as defined by Kline (2023), this study applies PLS-SEM to ensure a rigorous assessment of the measurement model. The structural model is tested to determine the direct relationships between the independent variables (Data Quality Management, Data Security, Ease of Use, and Top Management Support) and the dependent variable (Organizational Performance), using path coefficients and bootstrapping techniques.

Furthermore, it looks into the moderating influence of training on these interactions to see if it improves the impact of these factors on organizational performance. Finally, the chapter finishes with a review of the model's predictive relevance and effect size, summarizing the supported and unsupported hypotheses and their implications for the study's goals. This detailed investigation seeks to provide deeper insights into the elements that influence Big Data adoption and its impact on organizational performance.

4.2 Demographic Distribution of the Respondents

Data for this study were collected in two parts utilizing an online survey. The first phase was conducted from June 2021 to September 2023 (Phase I), followed by the second phase, which lasted from December 2023 to March 2024. The target companies were selected among the 428 active Global Business Services (GBS) companies with Malaysia Digital Status, as determined by the Malaysia Digital Economy Corporation (MDEC, 2022b). These companies were chosen based on their compatibility with MDEC's digital transformation initiative, which includes Big Data Analytics as a key focus area (PwC, 2021).

During Phase I, 100 questionnaires were given to persons at the selected GBS companies using a simple random sample technique. Out of these, 40 questionnaires were returned, yielding a 40% response rate (see Table 4.1). Respondents included C-Suite executives, middle managers, and data professionals (e.g., Data Analysts, Data Engineers, Data Administrators) working on Big Data plans, assuring a balanced representation of technical and strategic perspectives.

In Phase II, to increase the sample size and due to difficulties in obtaining responses in Phase I, an extra 600 questionnaires were sent via a convenience sampling approach. From this distribution, 232 questionnaires were returned, yielding a 39% response rate (refer to Table 4.2).

To ensure adequate responses and comprehensive representation across the targeted 201 companies, the study strategically distributed questionnaires to multiple individuals (2-5) within each selected company. This approach aimed to secure at least 2 completed responses per organization, enhancing the reliability of insights across different roles and perspectives within each company. Given the typical response rate challenges observed in management and technology studies, a larger dissemination strategy was also implemented, along with follow-up measures. Follow-up reminders were sent via email, LinkedIn, WhatsApp (Sekaran, 2003a), and phone calls (Salim Silva et al., 2002; Traina et al., 2005) to encourage participation and improve the overall response rate.

A total of 700 questionnaires were circulated across both phases, resulting in a final sample of 272 valid responses, or a 39% overall response rate. This exceeds the minimum required sample size (201 respondents) as stated in Krejcie and Morgan's (1970) table, as well as the minimal sample size of 129 proposed by G*Power analysis for a population this size. As a result, the obtained sample size ensures that the study's conclusions are statistically reliable and generalizable.

This is a valid response rate as indicated by Jobber (1989) statement regarding response rate. As illustrated in Table 4.1 and Table 4.2, there are no unusable questionnaires because all questionnaires have been completed. All returned questionnaires were useable questionnaires for further analysis. Therefore, a response rate of 39% is sufficient for this study, where Sekaran(2003a) had suggested that a response rate of 30% is sufficient for surveys. Furthermore, all returned questionnaires were fully completed, resulting in a 100% usability rate for future analysis with no missing data. This strategic approach allowed the study to collect extensive data despite external constraints like the COVID-19 pandemic.

Table 4.1
Phase I—Response Rate of the Questionnaires
(Date: June 2021 to Sept. 2023)

Response Rate of the Questionnaires	**Frequency & Rate**
Questionnaires distributed	100
Return and Usable Questionnaires	40
Returned and Excluded Questionnaires	0
Questionnaires with no return	60
Response Rate	40%
Valid Response Rate	40%

Table 4.2
Phase II—Response Rate of the Questionnaires
(Date: Dec. 2023 to Mar. 24)

Response Rate of the Questionnaires	**Frequency & Rate**
Questionnaires distributed	600
Return and Usable Questionnaires	232
Returned and Excluded Questionnaires	0
Questionnaires not Returned	368
Response Rate	39%
Valid Response Rate	39%

The demographic variables were classified into two parts which are respondents' profile as illustrated in Table 4.3. The first part includes six categories, which are gender, age, academic background, years or working experience, number of employees, and industry background. Meanwhile, the second part consists of six factors which are data quality management, data security, ease of use, top management support, training and organizational performance.

As illustrated in Table 4.3, the female respondents have a slightly higher response rate of 53.68% compared to 46.32% of male respondents. The majority of the respondents were aged 40-49 years old (33.09%), followed by respondents aged 30 to 39 (31.62%), 17.28% were aged below 29 years old, 13.60% were aged 50 to 59, and the lowest percentage, 4.41%, were aged 60 or above.

Regarding educational background, most of the respondents possess a bachelor's degree (65.44%), 28.68% of respondents possess a master's degree, 3.31% have a doctorate, and the remaining 2.57% have a diploma.

In terms of the type of industry, the top three industries based on respondents' demographic profiles were Oil and Gas (25.37%), Technology (16.18%), and Education (12.50%). Other industries include Government-Related Agencies (12.13%), Others (12.13%), Telecommunications (9.19%), Manufacturing (6.62%), and Financial Services (5.88%).

As for company size, 32.35% of respondents came from companies with more than 1000 employees, 24.26% from companies with 401-800 employees, 26.47% from companies with less than 200 employees, 9.56% from companies with 201-400 employees, and 7.35% from companies with 801-1000 employees.

Regarding job positions, the largest group of respondents was Professionals/Technical Experts (43.38%). The remaining respondents were Junior Analysts (20.96%), Middle Management (21.32%), and Senior Management/C-level (14.34%).

Table 4.3
Summary of Profiles of Respondent

Profiles of Respondents	Description	Frequency (N = 272)	Percentage
Gender	Male	126	46.32%
	Female	146	53.68%
Age	Below 29	47	17.28%
	30-39	86	31.62%
	40-49	90	33.09%
	50-59	37	13.60%
	60 or above	12	4.41%
Highest level of Education	Diploma	7	2.57%
	Bachelor	178	65.44%
	Master	78	28.68%
	Doctorate	9	3.31%
Industry	Oil and Gas	69	25.37%
	Technology	44	16.18%
	Education	34	12.50%
	Government Related Agencies	33	12.13%
	Others	33	12.13%
	Telecommunications	25	9.19%
	Manufacturing	18	6.62%
	Financial Services	16	5.88%
Years of Working Experience	Less than 5 years	15	5.51%
	5 to 10 years	34	12.50%
	11 to 20 years	139	51.10%
	More than 20 years	84	30.88%
Job Position	Professionals/Technical Experts	118	43.38%
	Supporting Staff/Junior Analyst	57	20.96%
	Middle Management	58	21.32%
	Senior Management/C-level	39	14.34%
Numbers of Employees	less or equal to 200	72	26.47%
	201- 400	26	9.56%
	401- 800	66	24.26%
	801 - 1000	20	7.35%
	More than 1000	88	32.35%

4.3 Data Screening and Preliminary Analysis

4.3.1 Data Coding

Data coding consists of two types regarding the categorization of data coding. For ease of identification and data analysis, the first category presumed that the code number should be assigned to each of the constructs (each variable). Secondly, the items would be included in the analysis, as every construct may have its own aspect of the questions. The questions should be organized in confirmatory with the construct (Blair, 2015). Therefore, the constructs used in the current study were coded as stated in Table 4.4.

Table 4.4
Variables Coding

Variables	Code
Data Quality Management	DM
Data Security	DS
Top Management	TM
Ease of Use	EOU
Organizational Performance	OP
Training	TNG

4.3.2 Missing Value Analysis

This study recorded no missing values, as data collection was conducted via an online platform. The online survey was designed to mandate that respondents complete all required measurement items prior to submitting their responses, thereby ensuring that no data fields remained unfilled. For a detailed review of the dataset, please refer to Appendix 2.

4.3.3 Assessment of Outliers

Tabachnick and Fidell (2013) stressed the importance of finding outliers, which are extreme responses to survey questions (Hair et al., 2017) or observations that differ greatly from the dataset's general trend (Zikmund et al., 2013. Outliers can disrupt data normalcy and potentially influence the results, leading to incorrect conclusions. Outliers in both independent and dependent variables must be detected and addressed in order to maintain data quality and validity (Hair et al., 2010).

Given the multivariate character of this investigation, Mahalanobis Distance was used to identify probable outliers (Hair et al. 2010). The assessment was conducted using SPSS Version 30, and the Mahalanobis Distance was employed to calculate the distance between each observation and a multidimensional space produced by all factors. Outliers are often indicated by values with a p-value of less than 0.001.

For this study, all Mahalanobis Distance values had p-values more than 0.001. As depicted in Table 4.5, the p-values ranged between 0.149 and 1.000, indicating that no outliers were found in the dataset. This shows that the data is homogeneous, and no observations were excluded from further analysis. The findings confirm that the dataset is suitable for further investigation without distortion from extreme values.

This analysis verifies the reliability of the results, as they are not influenced by anomalous data points that could have impacted the statistical power and validity of the study's conclusions.

Table 4.5
Mahalanobis Distance p_value

Description	Values
Total Observations Assessed	272
Range of Mahalanobis Distance p-values	0.149 – 1.000
Minimum p-value	0.149
Maximum p-value	1.000
Mean p-value	0.976
Outliers Detected (p-value < 0.001)	0

4.4 Test of Survey Bias

4.4.1 Non-Response Bias Test

Non-response bias occurs when there is a systematic difference between early and late respondents, compromising the validity of research (J. F. Hair et al., 2014). In this study, early respondents were those who responded within the first two weeks of receiving the initial invitation, whereas late respondents responded more than two weeks after receiving follow-up reminders.

To test for non-response bias, a Multi-Group Analysis (MGA) was performed in SmartPLS 4 using the Bootstrapping approach (J. Hair et al., 2017). The analysis evaluated at the structural relationships between early and late respondents to assess if their responses differed significantly. A bootstrapping approach was carried out in accordance with Henseler et al. (2015). This method provides for an extensive evaluation of the variations in path coefficients between the two groups.

The findings, as shown in Table 4.6, suggest that the variations in route coefficients between early (n=212) and late respondents(n=60) are minimal and statistically insignificant across all associations. A p-value larger than 0.05 is usually deemed statistically insignificant (Hair et al., 2017). In this investigation, each comparison generated a p-value of 1.00, which is significantly higher than the threshold, indicating that there are no differences.

The results of the Multi-Group Analysis (MGA) reveal that the differences in path coefficients between early and late respondents are minimal and statistically non-significant across all constructs. Specifically, the difference for the path from Data

Management (DM) to Organizational Performance (OP) is 0.08 with a p-value of 1.00, while Data Security (DS) to OP shows a difference of 0.33 and a p-value of 1.00. Similarly, the path from Ease of Use (EOU) to OP has a difference of -0.28 and a p-value of 1.00, and Top Management Support to OP has a difference of -0.23 with a p-value of 1.00. Finally, the path from Training (TNG) to OP indicates a difference of 0.02 with a p-value of 1.00. These consistently high p-values across all relationships confirm the absence of statistically significant differences between early and late respondents, suggesting that response timing did not influence the structural relationships within this study.

This consistency of results suggests that non-response bias is unlikely to be an issue in this study, as the key correlations between constructs do not differ significantly across early and late responders. Thus, the timing of responses does not appear to have a significant impact on the findings, which supports the study's conclusions.

Table 4.6
Multi-Group Analysis

Relationship	Difference (Early Respondents – Late Respondents)	1-tailed (Early Respondents vs Late Respondents) p value	2-tailed (Early Respondents vs Late Respondents) p value
DM -> OP	0.08	1.00	0.00
DS -> OP	0.33	1.00	0.00
EOU -> OP	-0.28	1.00	0.00
TM -> OP	-0.23	1.00	0.00
TNG -> OP	0.02	1.00	0.00

4.4.2 Common Method Bias

Common method bias (CMB) is a potential problem in survey-based research that occurs when measurement errors introduce systematic variance, overstated relationships between constructs and compromising the validity of findings (Philip M Podasakoff et al., 2003).

a) Full Collinearity Test

To solve this issue, the study used SmartPLS4's Variance Inflation Factor (VIF) values to measure full collinearity. According to Kock (2015), a VIF score less than 3.3 indicates that common method bias is not present in the model. In this investigation, all VIF values for the constructs were less than 3.3 as shown in Table 4.7, with the following results: DM -> OP (2.788), DS -> OP (1.689), EOU -> OP (1.995), TM -> OP (2.654), and TNG -> OP (2.204). Thus, the findings indicate that common method bias is not a concern, confirming the data's robustness and reliability.

Table 4.7
Full Collinearity Test

Relationship	VIF
DM -> OP	2.788
DS -> OP	1.689
EOU -> OP	1.995
TM -> OP	2.654
TNG -> OP	2.204

b) Harman's Single-Factor Test

Common Method Variance (CMV) is the variance that is attributable to the measurement method rather than the constructs that the measures represent (Podsakoff & Organ, 1986). This type of bias can occur when data for both the independent and dependent variables are collected from the same source, with the same measurement instrument, or at the same time, potentially resulting in inflated correlations between variables (Philip M Podasakoff et al., 2003; Saxena et al., 2022).Podsakoff et al. (2012) found that CMV can seriously undermine the validity of study findings, particularly in self-reported surveys, where perceptual biases might distort the correlations between constructs. .

To ensure that CMV did not have a substantial impact on the study's outcomes, Harman's Single-Factor Test was used, as recommended by Podsakoff & Organ, (1986). This test entails running an exploratory factor analysis (EFA) to see if a single factor explains for the bulk of the variance between the variables. The reasoning behind this test is that if one factor accounts for more than half of the variance, it indicates the presence of a common technique bias.

In this investigation, Harman's Single-Factor Test revealed that the first factor accounted for 38.56% of total variation, which is less than the 50% threshold given , as recommended by Philip M Podasakoff et al. (2003). Therefore, the current study reveals that Common Method Variance is not a major concern and uunlikely to pose a significant issue, as illustrated in the Table 4.8.

Table 4.8
Harman's Single-Factor Test

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	16.78	39.95	39.95	16.19	38.56	38.56
2	3.58	8.51	48.47			
3	2.95	7.03	55.50			
4	2.02	4.81	60.31			
5	1.17	2.79	63.10			
6	1.14	2.73	65.83			
7	1.01	2.40	68.23			
8	0.92	2.19	70.43			
9	0.87	2.07	72.49			
10	0.79	1.88	74.38			
11	0.77	1.83	76.21			
12	0.66	1.58	77.79			
13	0.64	1.51	79.30			
14	0.57	1.36	80.66			
15	0.55	1.30	81.96			
16	0.53	1.25	83.21			
17	0.50	1.20	84.41			
18	0.46	1.10	85.52			
19	0.44	1.06	86.57			
20	0.43	1.03	87.60			
21	0.40	0.94	88.54			
22	0.38	0.91	89.46			
23	0.35	0.84	90.30			
24	0.32	0.76	91.06			
25	0.31	0.75	91.81			
26	0.29	0.70	92.51			
27	0.29	0.70	93.21			
28	0.28	0.66	93.86			
29	0.26	0.61	94.48			
30	0.24	0.57	95.05			
31	0.24	0.56	95.61			
32	0.22	0.52	96.13			
33	0.22	0.52	96.65			
34	0.21	0.50	97.14			
35	0.20	0.47	97.62			
36	0.17	0.42	98.04			
37	0.17	0.40	98.44			
38	0.16	0.38	98.82			
39	0.14	0.34	99.16			

40	0.13	0.31	99.48
41	0.11	0.27	99.75
42	0.10	0.25	100.00

4.5 Descriptive Statistics

Descriptive statistics are the simple quantitative summary of a data set (Appendix 3) shows a descriptive statistic of the construct where it summarizes the data of construct. This involves Data Quality Management (DM), Data Security (DS), Top Management Support (TM), Ease of Use (EOU), Organizational Performance (OP), and Training (TNG) from the respondents' perspective, whereby N are the value for minimum, maximum, mean and standard deviation of the constructs.

As illustrated in (Appendix 3), the minimum value and the maximum value for all the items was 1.00 and 5.00 respectively, by using Likert Scale. All 39 items had a high mean value where it indicated that respondents have high acceptance of overall constructs. As tabulated in Appendix 3, the standard deviation is between 0.711 to 1.066, whereby the standard deviation for Data Quality Management (DM) is between 0.836 and 1.039, Data Security (DS) is between 0.871 and 0.995, Ease of Use is between 0.760 and 0.933, Top Management Support is between 0.965 and 1.066, Organizational Performance (OP) is between 0.760 and 0.880, and training is between 0.711 and 0.967. The results show that all 39 items had a small value of standard deviation where it indicated that most of the data were clustered around the mean.

4.5.1 Descriptive Statistics by Industry

When analyzing organizational performance, it is crucial to analyze how different industries handle critical elements and usability. This analysis compares statistically at how businesses such as telecommunications, technology, oil and gas, and government-related agencies perform on a variety of parameters. By evaluating data from several industries, improvement can be determined by analyzing the patterns, and variability range.

To analyze these variables, descriptive statistics were employed, focusing on the central tendency (median) and the spread of the data (Interquartile Range - IQR). These statistical methods were executed using SPSS version 30 to provide a clear comparison of performance across industries.

Organizational Performance (OP_AVG)

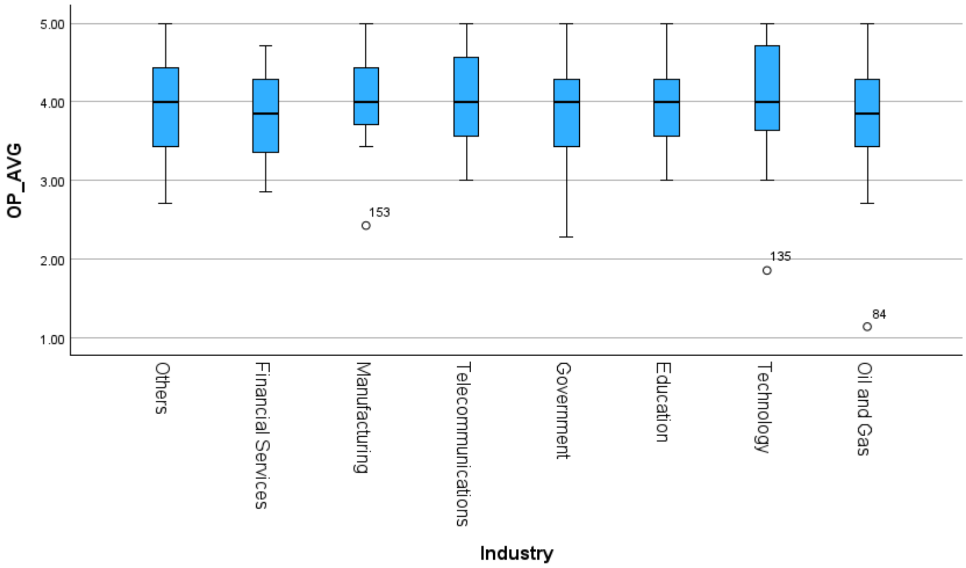

Figure 4.1
Box Plot Analysis Organizational Performance (OP_AVG)

As depicted in Figure 4.1, the telecommunications sector stands out for its consistent performance high median scores and low variability, as companies in this sector have adopted a forward-thinking approach to technology and innovation. Maxis Berhad, a notable example of digital transformation leadership. Maxis has regularly excelled peers in operational performance for its dedication to digital innovation. Maxis was recognized in 2022 as a Top Employer in Malaysia by the Top Employers Institute (Maxis, 2022), further validating its strong organizational culture . This recognition highlights Maxis' success in fostering an environment that prioritizes employee well-being, innovation, and continuous learning.

Whereas sectors such as oil and gas indicates lower with performance, owing to operational complexity, reliance on legacy IT systems (DQLabs, 2024; McKinsey & Company, 2022; Summit, 2023).

Data Quality Management (DM_AVG)

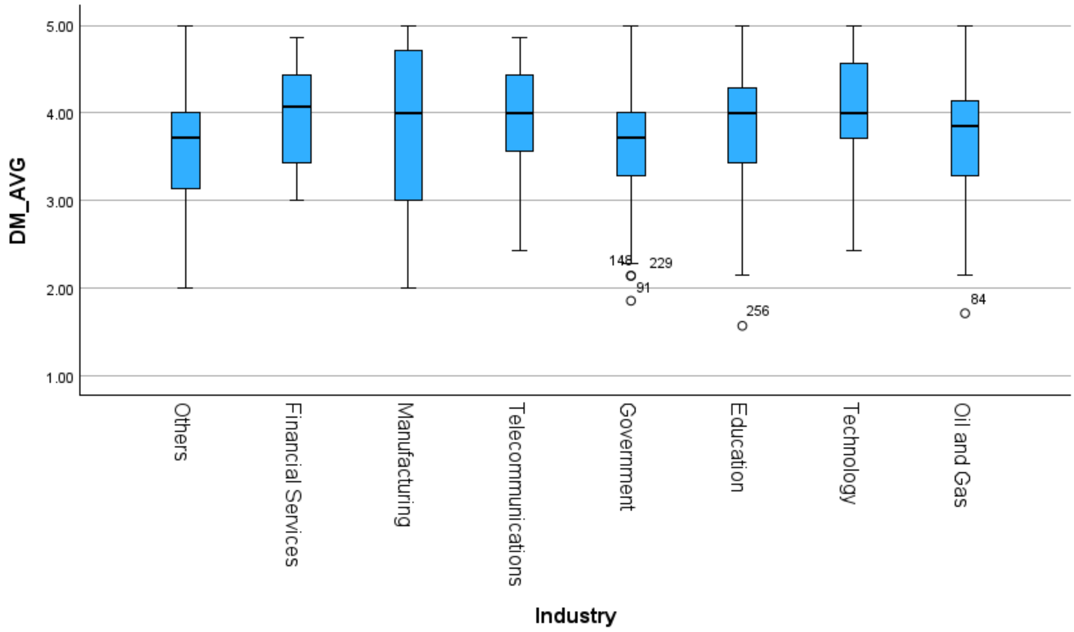

Figure 4.2
Box Plot Analysis Data Quality Management (DM_AVG)

As depicted in Figure 4.2, manufacturing leads with the highest median, though it exhibits wide variability, reflecting strong performers in Data Quality Management. For example, Top Glove's leadership in quality data management and its adoption of big data practices have been crucial to maintaining its reputation for excellence in manufacturing. By leveraging advanced data analytics, the company has optimized quality control, predictive maintenance, and supply chain efficiency. These data-driven strategies have supported its industry recognition, such as the Platinum Trusted Brand Award in 2024 (Business News, 2024) emphasizing its commitment to quality and reliability.

On the other hand, Oil and gas and government-related agencies have lower medians and greater variability, challenges with data integration and management due to fragmented systems and dependency with legacy infrastructure (DQLabs, 2024; Open

Access Government, 2023) . This hinders efforts to improve operational efficiency in these sectors.

Data Security (DS_AVG)

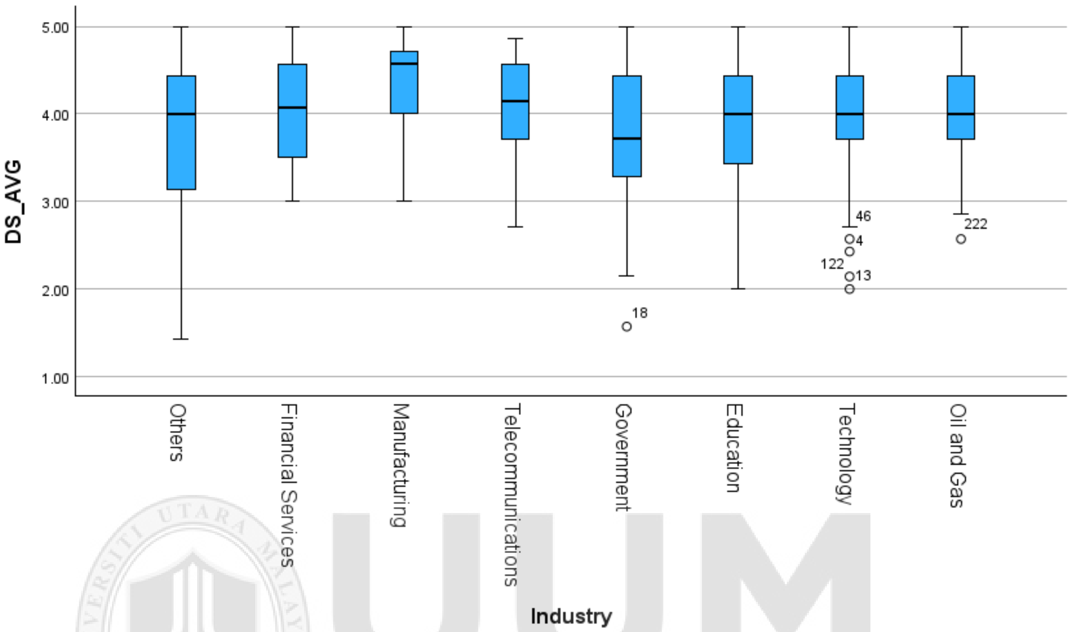

Figure 4.3
Box Plot Analysis Data Security (DS_AVG)

As depicted in Figure 4.3, financial services maintain the highest median score in data security, with narrow variability, indicating robust compliance and regulatory frameworks for consistent data protection. Notably, HSBC Global Service Centre Malaysia, a renowned Malaysia Digital Status financial service provider in the Global Business Services (GBS) sector, illustrates these requirements. HSBC Malaysia is known for its excellent cybersecurity standards, which include sophisticated encryption techniques, safe authentication processes, and extensive data loss prevention strategies. These measures demonstrate their great commitment to protecting sensitive information and following local and international data protection requirements.

In acknowledgment of these efforts, HSBC Malaysia awarded Asiamoney's Best International Bank Award in 2019 (Milne & Officer, 2019), showcasing their leadership in financial security and compliance. This recognition highlights HSBC's dedication to maintaining strong data security standards, reinforcing the financial sector's position as a leader in regulatory compliance and data protection.

On the other hand, oil and gas and government-related agencies indicate lower medians with greater variability. The presence of fragmented data systems and outdated security methods in many industries makes it challenging to maintain consistent data security standards. However, these sectors are often more risk-averse, favoring stability and caution in adopting newer technologies (McKinsey & Company, 2022).

Ease of Use (EOU_AVG)

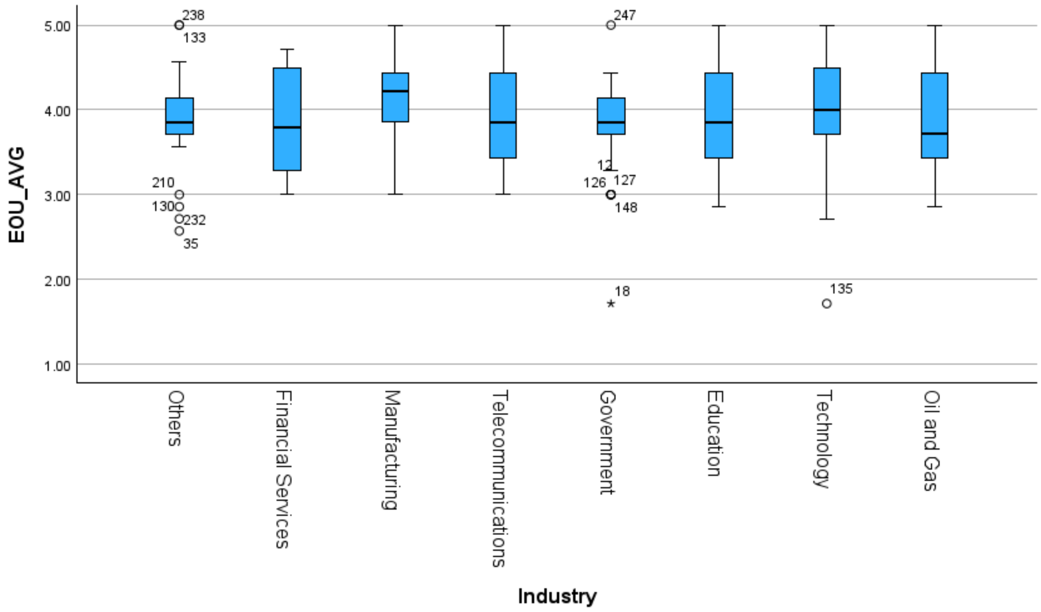

Figure 4.4
Box Plot Analysis Ease of Use (EOU_AVG)

As depicted in Figure 4.4, the education sector shows the highest median score with the least variance for EOU_AVG, reflecting consistent and favorable adoption of user-friendly technologies across the industry. For example, MDEC has acknowledged Asia Pacific University (APU) for its contributions to the advancement of digital education and skills. MDEC has recognized APU as a Premier Digital Tech Institution (PDTI) after it obtained Malaysia Digital designation (Asia Pacific University of Technology & Innovation, 2023). This certification recognizes APU's efforts to cultivate digital talent, integrate its curriculum with industry demands, and prioritize digital transformation programs that are particularly relevant in the Global Business Services (GBS) sector.

In contrast, the others category demonstrates the lowest median and the highest variance, indicating significant inconsistencies, likely due to varied operational contexts and challenges in standardizing technology usability.

Top Management Support (TM-AVG)

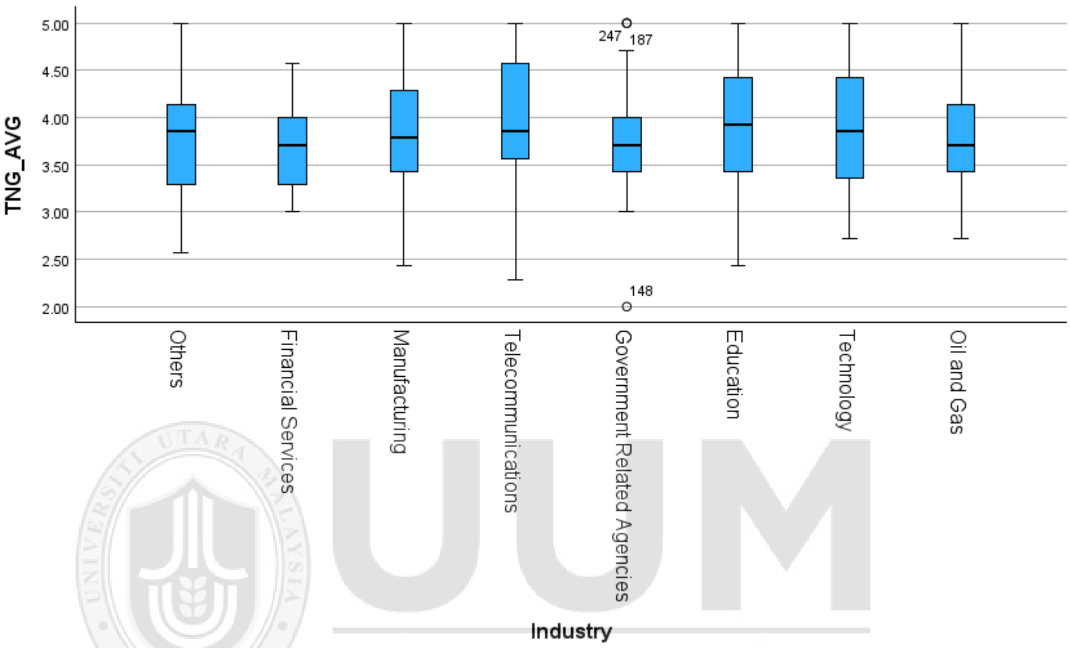

Figure 4.5
Box Plot Analysis Top Management Support (TM_AVG)

As depicted in Figure 4.5, the telecommunications industry has the highest median score with relatively low volatility for top management support, showing strong and consistent top management support for technological efforts. This demonstrates the sector's commitment to digital transformation and ongoing investment in infrastructure and innovation. For example, Malaysian telecommunications businesses such as Maxis and Telekom Malaysia have been at the forefront of driving digital transformation, not just within their organizations but also in pushing digital adoption across multiple industries (Maxis, 2022; MIDA, 2020). Their efforts to improve networks and integrate emerging technologies demonstrate leadership that supports long-term digital development.

In contrast, the government sector had a lower median score and a broader interquartile range, indicating variation in management assistance. The slow adoption of technology and inconsistencies in leadership alignment within Government-Related Agencies in Malaysia are often linked to the bureaucratic structures that dominate the public sector (Junaidi & Jaes, 2023; Lim, 2007; Open Access Government, 2023). These structures not only slow down decision-making but also make it difficult for leadership to adapt quickly to technological changes.

Training (TNG_AVG)

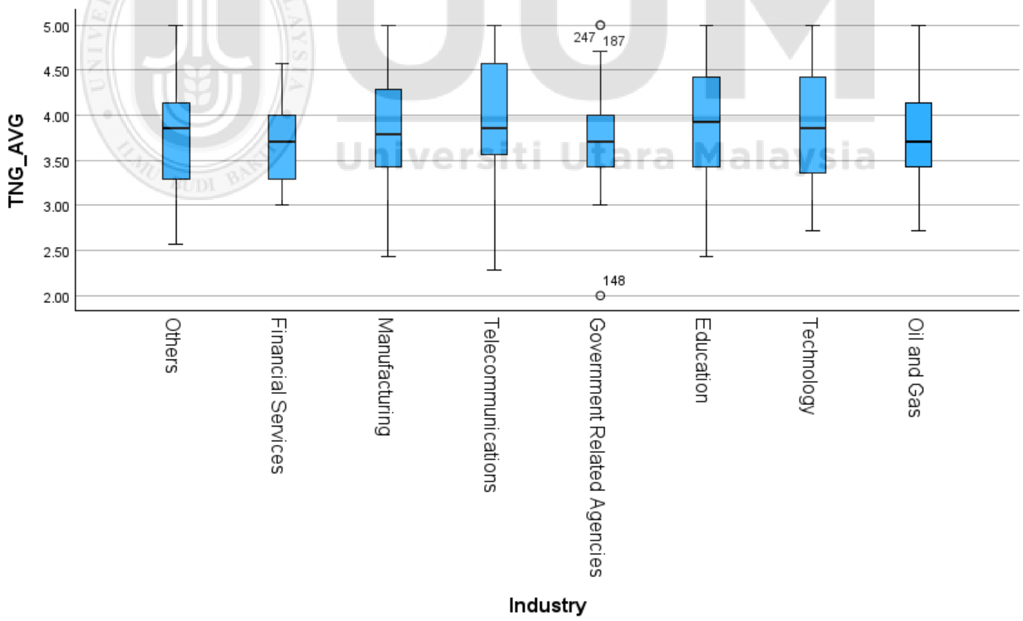

Figure 4.6
Box Plot Analysis Training (TNG_AVG)

As depicted in Figure 4.6, the telecommunications and technology industries had the highest median training scores with relatively low variability, indicating a constant and strong commitment to staff development. This shows that these industries place a premium on continuous skill development, which is critical to sustaining a competitive advantage. Notably, Axiata Group, a leading telecommunications and technology company has received recognition for its major contributions to workforce upskilling.

Axiata Group was recognized for its Axiata Digital Labs initiative, which aims to cultivate digital talent through specialized training programs in software engineering, data analytics, and cybersecurity. These efforts are highlighted in the Axiata Sustainability and National Contribution Report (2021), which underlines the company's involvement in talent development as part of its sustainability goals and digital transformation plan. This commitment demonstrates Axiata's leadership in fostering digital transformation.

In contrast, the Government-Related Agencies and Education sectors have lower median scores with broader variances, indicating inconsistent training processes. This disparity emphasizes the need for more structured and effective training programs in these areas, whose performance lags behind more agile sectors like technology (Junaidi & Jaes, 2023).

In conclusion, the analysis shows that the telecommunications and technology sectors continuously lead in a variety of performance measures, including organizational performance, data quality management, data security, ease of use, and training. These sectors have high median scores with little variability, indicating a purposeful focus on technological adoption, consistent procedures, and ongoing investment in workforce development. Conversely, sectors such as oil & gas and government related agencies have lower median ratings and greater variability. These issues originate from operational complexities, dependence on legacy systems, combined with the inherent volatility of the sector, and fragmented data practices, which impede efforts to streamline and modernize processes efficiently (DQLabs, 2024; Junaidi & Jaes, 2023; McKinsey & Company, 2022; Open Access Government, 2023; Summit, 2023).

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4.6 Assessment of Measurement Model

4.6.1 Assumption of Normality

Appendix 4 presents the result of skewness and kurtosis that represent normality, presents the result of skewness and kurtosis that represent normality, where the value of skewness that range between -0.817 and -0.373 is acceptable as suggested by Hair et. al. (2019) (+1 to -1). Meanwhile, the value of kurtosis is between -0.639 and 0.649 also is acceptable as suggested by Coakes et al. (2008) (+3 to -3). In conclusion, all constructs used in this study were normally distributed.

4.6.2 Test of Linearity

The researcher utilized the scatterplot builder feature in SPSS to assess the linearity patterns among the variables. The resulting plots demonstrated a clear upward trend, indicative of a straight-line relationship between the variables, which supports the positive relationship between the dependent and the independent variables. Furthermore, when the moderator variable is plotted against both the independent and dependent variables, it shows an upward trend, indicating that training could positively influence these relationships.

The scatterplots (Figure 4.7) do not exhibit any systematic patterns or curvature that would suggest a violation of linearity. The data points show a constant upward trend, which supports the linear relationship between variables. Furthermore, there is no evidence of heteroscedasticity, such as uneven point distribution or clustering, which could imply outlier-driven distortion. This similar pattern across all scatterplots supports the idea of a linear relationship between the variables. As a result, linearity is satisfied, and the model can be confidently employed for future research.

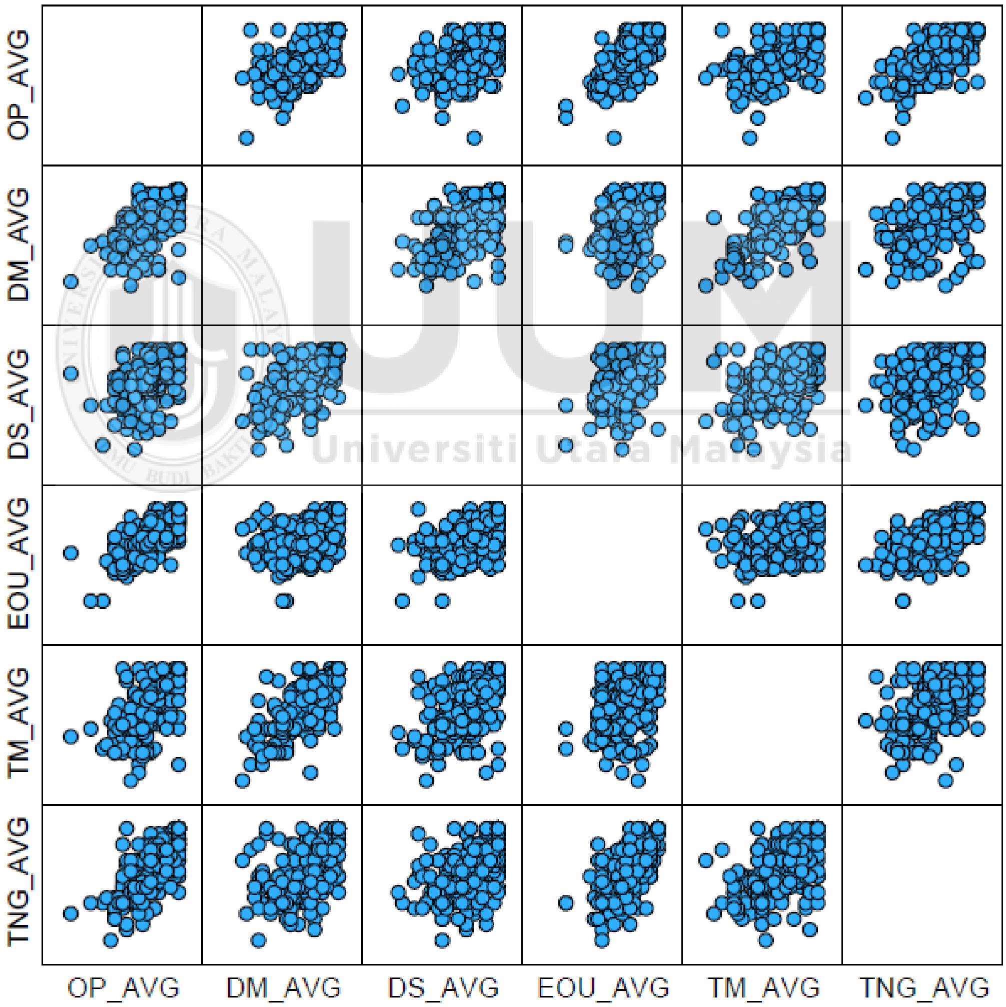

Figure 4.7
Linearity Scatter Plot

4.7 Testing the Measurement, Outer Model Using PLS Approach

Figure 4.8 shows the PLS Measurement Model diagram of this study.

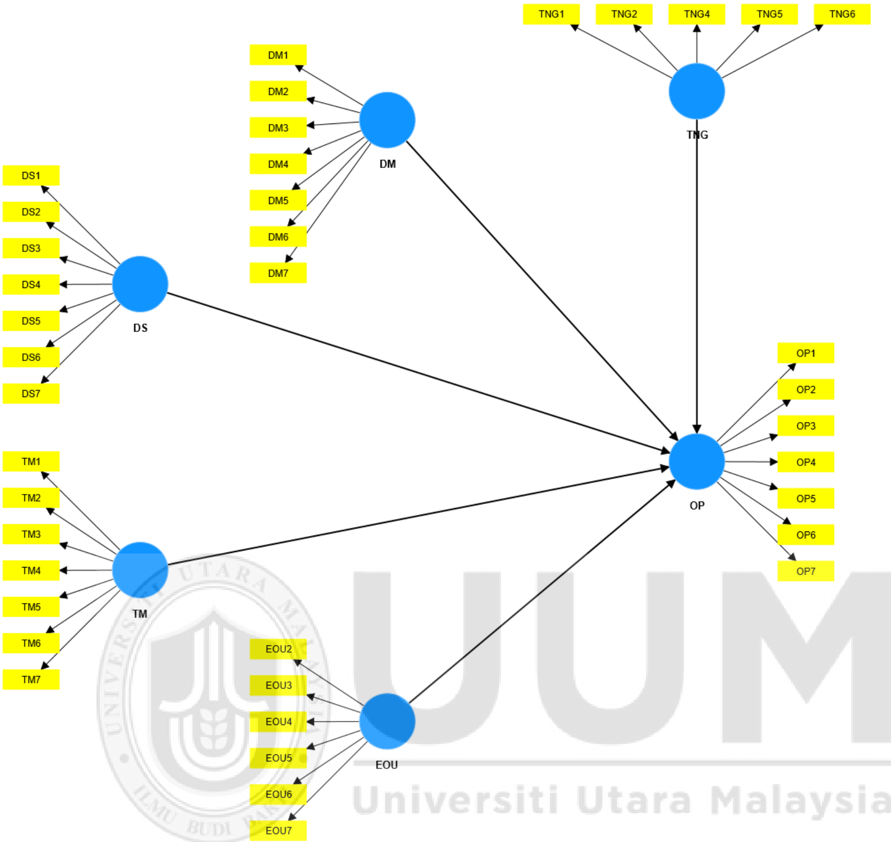

Figure 4.8
PLS Measurement Model

4.7.1 The Construct Validity

According to Hair et al. (2006), construct validity can be assessed through the content validity, convergent validity, and discriminant validity.

4.7.2 The Content Validity

Based on the factor analysis, all items were correctly allocated to their constructs. Hair et al. (2014) stated that items with loadings ranging from 0.4 and 0.7 should be retained. Barclay et al. (1995) and Chin W (1998) also accepted loadings that are equal to 0.4. With regard to all studies, researchers accept the items that have loading of 0.4 and more than 0.7. Thus, as illustrated in Appendix 5 and Appendix 6) all 39 items were retained because the loadings between 0.569 and 0.886 (see Appendix 5). It is showed that the loadings for data quality management range is between 0.637 and 0.851, data security range is between 0.689 and 0.879, Ease of Use range is between 0.569 and 0.844, Organization performance is 0.777 and 0.847, Top management support range is between 0.796 and 0.886, training range is between 0.702 and 0.807.

Furthermore, multicollinearity was not a major concern since the squared correlations between the constructs in the correlation matrix are less than 0.8. Additionally, the variance inflation factors in the collinearity diagnostics are less than the threshold value of 10 (Hair et al., 2006) as indicated in Appendix 5. Thus, the result shows that the multicollinearity assumption was not violated.

4.7.3 The Convergent Validity

As suggested by Hair (2009), to establish the convergent validity, three criteria should be tested simultaneously, namely the factor loadings, composite reliability (CR), and average variance extracted (AVE). Regarding the factor loadings, the researcher accepts the items that have loading of 0.4 and more than 0.7. In this study, all 39 items remain because loadings are between 0.569 and 0.8886 (see Appendix 5& 6).

The Cronbach’s alpha values ranged from 0.811 to 0.938, and the Composite Reliability values ranged from 0.869 to 0.950, both exceeding the recommended threshold of 0.7 (Fornell & Larcker, 1981; Hair et al., 2014). Specifically, Cronbach's alpha values were 0.896 for data quality management, 0.907 for data security, 0.830

for ease of use, 0.938 for top management support, 0.912 for organizational performance, and 0.811 for training. Additionally, the Composite Reliability values were 0.919 for data quality management, 0.927 for data security, 0.878 for ease of use, 0.950 for top management support, 0.930 for organizational performance, and 0.869 for training. These results indicate that convergent validity for the outer model has been established.

Additionally, the Average Variance Extracted (AVE) values were assessed to verify the convergent validity of the outer model. Hair et al. (2014) recommends using AVE as a common method for this purpose. Table 4.9 shows that all AVE values fall within the acceptable range of 0.548 to 0.731, indicating that convergent validity has been achieved. Specifically, the AVE values are 0.621 for data quality management, 0.646 for data security, 0.548 for ease of use, 0.731 for top management support, 0.655 for organizational performance, and 0.570 for training. Thus, convergent validity has also been confirmed.

Table 4.9

The Convergent Validity Analysis

Factor	Item	Cronbach's alpha	Composite reliability	Average Variance Extracted (AVE)
Data quality management (DM)	7	0.896	0.919	0.621
Data Security (DS)	7	0.907	0.927	0.646
Ease of Use (EOU)	6	0.830	0.878	0.548
Top Management Support (TM)	7	0.938	0.950	0.731
Organizational Performance (OP)	7	0.912	0.930	0.655
Training (TNG)	5	0.811	0.869	0.570

4.7.4 The Discriminant Validity

This study assessed the discriminant validity by using the method of Fornell & Larcker (1981). The discriminant validity of the outer model for this study was confirmed where the diagonal elements in the table were higher than the other elements of the column and row in which they are located in Table 4.10 as indicated by Fornell & Larcker (1981). Based on the result, the discriminant validity has been met.

Table 4.10

Discriminant Validity Fornell & Larcker Criterion

Constructs	DM	DS	EOU	OP	TM	TNG
Data quality management (DM)	0.788					
Data Security (DS)	0.582	0.804				
Ease of Use (EOU)	0.430	0.481	0.74			
Organizational Performance (OP)	0.625	0.541	0.722	0.809		
Top Management Support (TM)	0.768	0.514	0.437	0.628	0.855	
Training (TNG)	0.52	0.451	0.679	0.73	0.551	0.755

Discriminant validity also involves analyzing the Heterotrait-Monotrait Ratio (HTMT) of correlations by using PLS-SEM (Ringle et al., 2014). High HTMT values indicate discriminant validity problems (Hair et al., 2013). Henseler et al. (2015) suggested a threshold value of 0.90 if the path model includes items which are conceptually quite the same. Therefore, HTMT value exceeding 0.90 indicates a lack of discriminant validity. However, when the constructs in the path model are conceptually more distinct, researchers should consider 0.85 as the threshold for HTMT (Henseler et al., 2015). Table 4.11 shows discriminant validity for Heterotrait-Monotrait Ratio whereby all the results are clearly below or at the conservative threshold of 0.85 and the discriminant validity has been met. Thus, the result reported that there is discriminant validity. The factor loadings and cross-loadings for every item are also shown in Table 4.12, which offers more proof of discriminant validity. The findings in Tables 4.11 and 4.12 collectively attest to the measurement model's resilience and validate that the analysis's discriminant validity requirements have been well satisfied.

Table 4.11
Discriminant Validity: Heterotrait-Monotrait Ratio

Constructs	**DM**	**DS**	**EOU**	**OP**	**TM**	**TNG**
Data quality management (DM)						
Data Security (DS)	0.647					
Ease of Use (EOU)	0.503	0.563				
Organizational Performance (OP)	0.691	0.594	0.832			
Top Management Support	0.836	0.558	0.499	0.677		
Training (TNG)	0.611	0.529	0.83	0.847	0.631	

Table 4.12

Factor Loading/Cross Loading

Items	DM	DS	EOU	OP	TM	TNG
DM1	**0.637**	0.338	0.440	0.457	0.486	0.386
DM2	**0.849**	0.436	0.355	0.519	0.647	0.447
DM3	**0.795**	0.434	0.325	0.499	0.543	0.405
DM4	**0.824**	0.395	0.308	0.502	0.698	0.435
DM5	**0.807**	0.518	0.285	0.478	0.577	0.381
DM6	**0.851**	0.547	0.346	0.498	0.718	0.433
DM7	**0.731**	0.534	0.315	0.487	0.546	0.373
DS1	0.398	**0.709**	0.424	0.430	0.316	0.384
DS2	0.412	**0.689**	0.339	0.408	0.369	0.361
DS3	0.486	**0.852**	0.395	0.445	0.442	0.348
DS4	0.493	**0.860**	0.405	0.453	0.421	0.351
DS5	0.508	**0.879**	0.394	0.434	0.450	0.387
DS6	0.479	**0.778**	0.378	0.423	0.462	0.348
DS7	0.487	**0.836**	0.363	0.440	0.425	0.357
EOU2	0.301	0.42	**0.569**	0.482	0.329	0.441
EOU3	0.292	0.408	**0.772**	0.534	0.279	0.493
EOU4	0.299	0.383	**0.688**	0.482	0.366	0.445
EOU5	0.331	0.385	**0.844**	0.576	0.291	0.567
EOU6	0.367	0.305	**0.831**	0.592	0.353	0.518
EOU7	0.314	0.249	**0.702**	0.526	0.329	0.536
OP1	0.591	0.514	0.556	**0.799**	0.583	0.615
OP2	0.579	0.572	0.501	**0.785**	0.58	0.576
OP3	0.518	0.424	0.631	**0.831**	0.512	0.626
OP4	0.452	0.439	0.623	**0.847**	0.502	0.590
OP5	0.416	0.349	0.628	**0.829**	0.428	0.561
OP6	0.513	0.36	0.555	**0.777**	0.483	0.572
OP7	0.464	0.395	0.596	**0.794**	0.458	0.590
TM1	0.636	0.386	0.399	0.534	**0.832**	0.477
TM2	0.651	0.454	0.330	0.508	**0.796**	0.423
TM3	0.707	0.461	0.427	0.563	**0.884**	0.556
TM4	0.688	0.474	0.382	0.532	**0.88**	0.481
TM5	0.627	0.404	0.354	0.52	**0.872**	0.451
TM6	0.597	0.406	0.298	0.525	**0.832**	0.438
TM7	0.683	0.491	0.417	0.569	**0.886**	0.468
TNG1	0.468	0.324	0.434	0.578	0.561	**0.737**
TNG2	0.41	0.44	0.434	0.522	0.485	**0.702**
TNG4	0.312	0.344	0.626	0.561	0.285	**0.807**
TNG5	0.424	0.229	0.563	0.539	0.394	**0.784**
TNG6	0.348	0.37	0.502	0.551	0.354	**0.741**

Note: DM=Data quality management, DS=Data Security, EOU=Ease of Use, OP=Organizational Performance, TM=Top Management Support, TNG=Training.

4.8 Structural Model Assessment and Moderating Effect Analysis

4.8.1 Hypothesis Testing for the Inner Structural Model

Once the validity of the outer model has been confirmed, the next stage was to test the hypothesized relationships among the variables. By running PLS bootstrapping using SmartPLS 4, the hypothesized model was tested. Therefore, the T Statistics were generated to test all hypotheses as illustrated in Table 4.13. The threshold value of T Statistics for one tail test is 1.645. Therefore, hypothesis which falls above 1.645 should be accepted, while hypothesis which falls below 1.645 should be rejected (Tomczak et al., 2014).

Figure 4.9 shows path model significance result for this study, where the T Statistics between data quality management and organizational performance indicate a positive relationship of 2.190. Next, the T Statistics between data security and organizational performance indicate not a positive relationship which is 1.066 (below than 1.645). In contrast, the T Statistics between ease of use and organizational performance indicates a positive relationship of 6.391 which is the most significant on positive relationship. Lastly, T Statistics between top management support and organizational performance also indicate a positive relationship of 2.483.

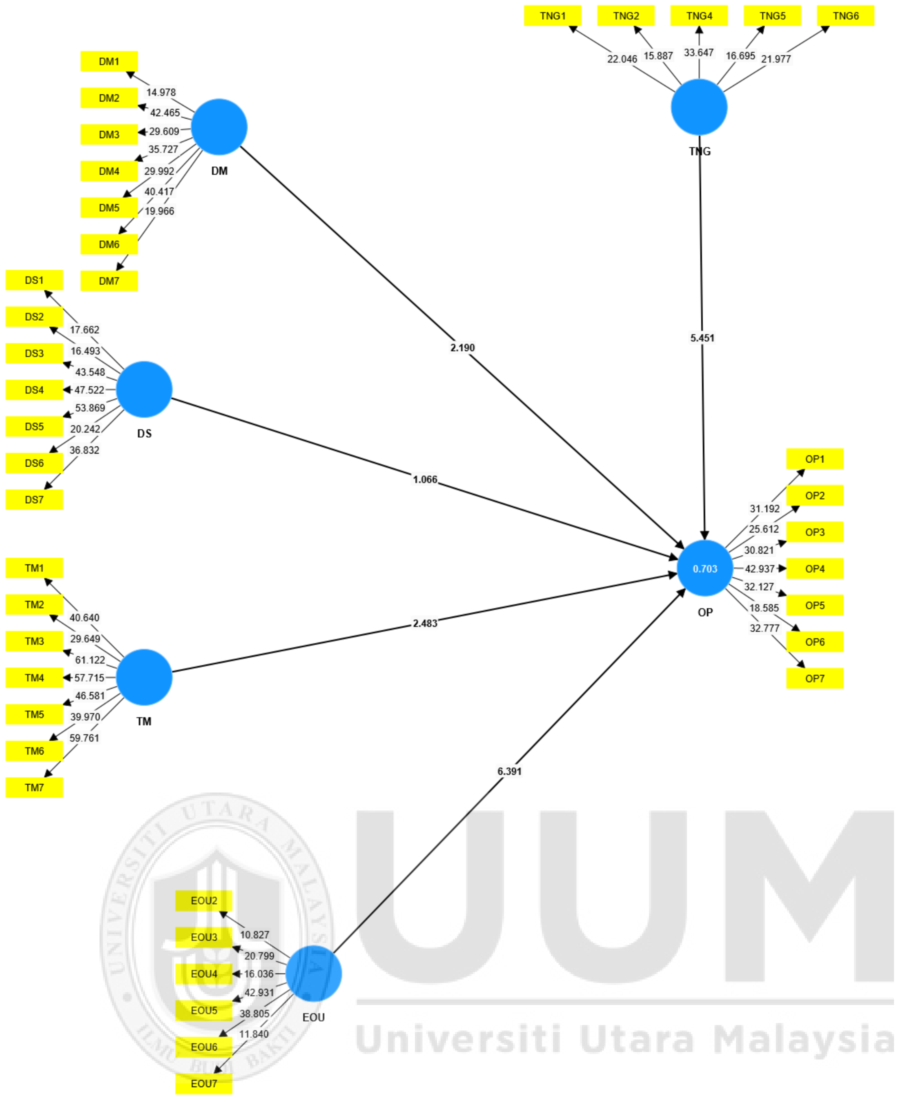

Figure 4.9
Path Model Significance Result

To conclude whether the relationships among the variables are statistically significant or not, bootstrapping techniques using SmartPLS 4 were used in this study. Most studies employ 0.05 as the threshold value of the level of significance, p-value (Tomczak et al., 2014).

As indicated in Table 4.13, the results showed data quality management has a significantly positive effect on the organizational performance (β=0.17, t=2.19, p=0.029), because the T Statistics is 2.19 (>1.645) at $p < 0.05$ (5% significance).

Therefore, the hypothesis (H1) on the effect of data quality management and organizational performance was accepted. On the other hand, data security has no positive relationship with significant effect on the organizational performance (β=0.063, t=1.066, p=0.286). Therefore, the hypothesis (H2) was not accepted. Furthermore, ease of use has a positive relationship with significant effect on the organizational performance (β=0.359, t=6.391, p=0.000). Therefore, hypothesis (H3) has been accepted. Moreover, the top management support has a positive relationship with significant effect on the organizational performance (β=0.15, t=2.483, p=0.013). Hence, hypothesis (H4) of the effect of top management support on organizational performance has been accepted.

The outcomes of the 4 hypotheses having direct relationships are described below:

a) H1: There is positive significance between data quality management in Big Data adoption and organizational performance. (β=0.17, T=2.19, p-value=0.029).

b) H2: There is no positive significance between data security in Big Data adoption and organizational performance. (β=0.063, T=1.066, p-value=0.286).

c) H3: There is positive significance between ease of use in Big Data adoption and organizational performance. (β=0.359, T=6.391, p-value=0.000).

d) H4: There is positive significance between top management support in Big Data adoption and organizational performance. (β=0.15, T=2.483, p-value=0.013).

Table 4.13
The Result of the Inner Structural Model

Hypothesis	Relationship	Standard Beta	Standard Deviation	T statistics	p-values*	Decision
H1	(DM) → (OP)	0.170	0.078	2.19	0.029	Supported
H2	(DS) → (OP)	0.063	0.059	1.066	0.286	Not Supported
H3	(EOU) → (OP)	0.359	0.056	6.391	0.000	Supported
H4	(TM) → (OP)	0.150	0.060	2.483	0.013	Supported

Note: *p < 0.05 (T Statistics> 1.645) for 1-tailed test. DM=Data quality management, DS=Data Security, EOU=Ease of Use, OP=Organizational Performance, TM=Top Management Support, TNG=Training.

4.8.2 Hypothesis Testing for Moderating Effect of Training

In this study, SmartPLS 4 was utilized for testing the moderating effect of Training. Figure 4.10 shows the model of moderating effect of training between Data quality management and Organizational Performance, whereby it indicates no positive relationship with the T Statistics at 1.379. Meanwhile Figure 4.11 shows the model of moderating effect of training between Data Security and Organizational Performance, and it indicates no positive relationship with the T Statistics at 1.221. Furthermore, Figure 4.12 shows the model of moderating effect of training between Ease of Use and Organizational Performance indicates a positive relationship with the T Statistics at 1.854. Lastly, Figure 4.13 shows the model of moderating effect of training between Top Management Support and Organizational Performance, whereby it indicates no positive relationship with the T Statistics at 0.587. With this result, only Ease of Use indicates positive relationship for the model of moderating effect of training and Organizational Performance as depicted in figure 4.12.

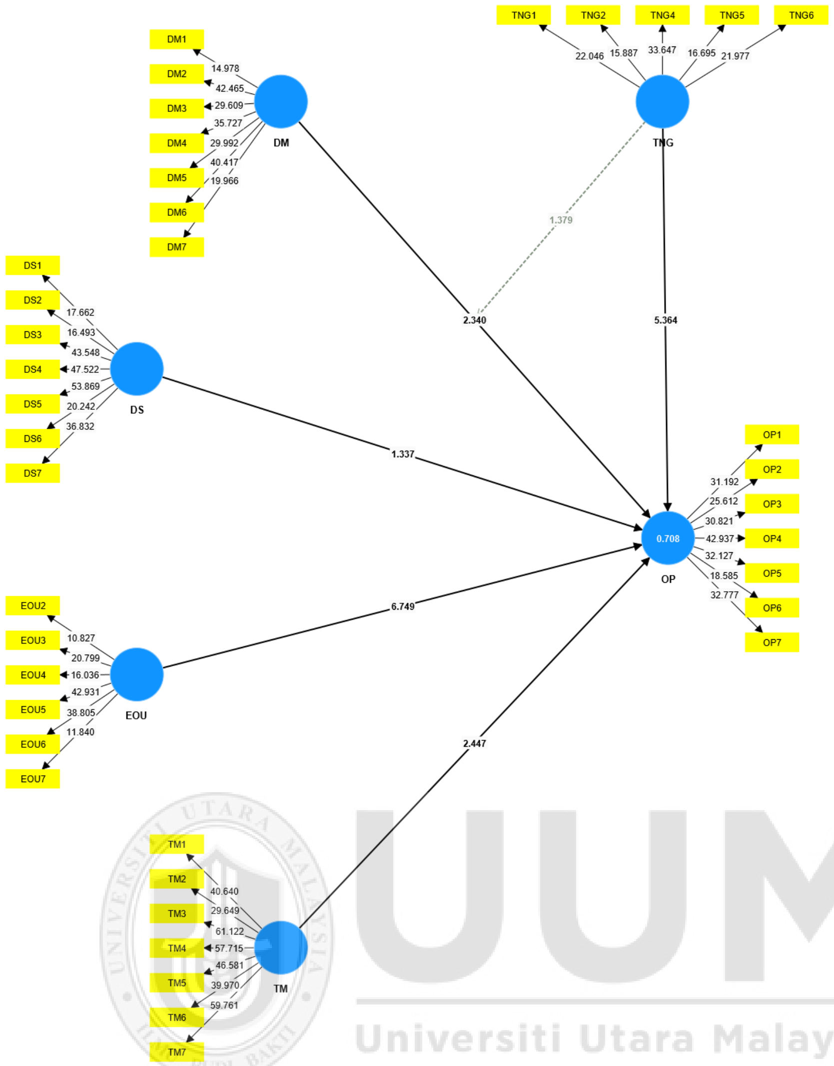

Figure 4.10
Model of Moderating Effect of Training between Data Quality Management and Organizational Performance

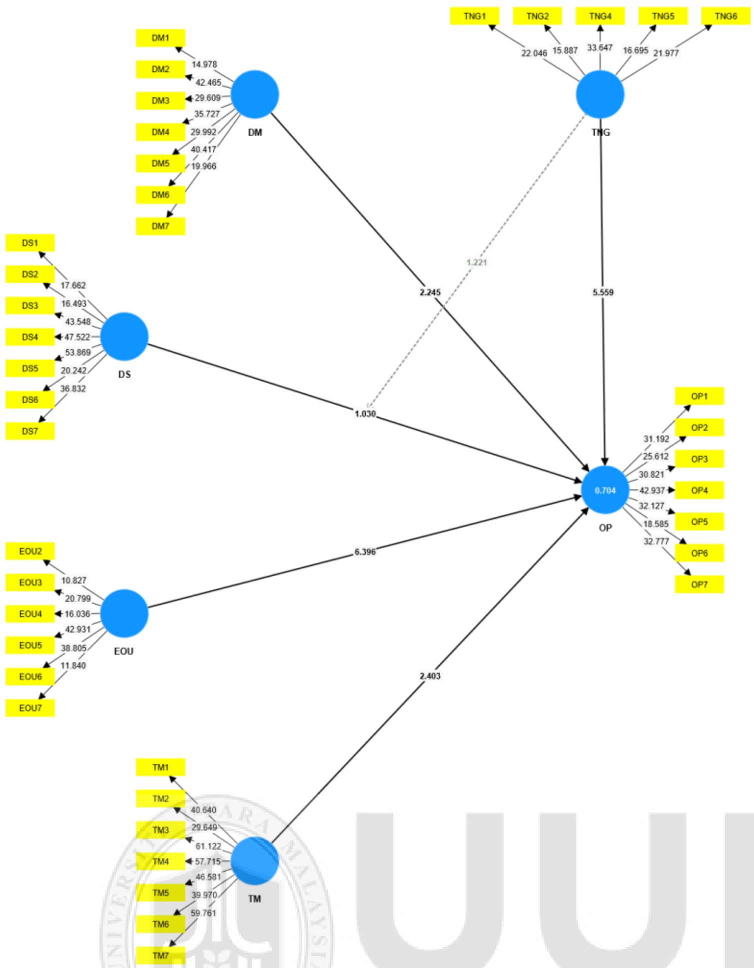

Figure 4.11
Model of Moderating Effect of Training between Data Security and Organizational Performance

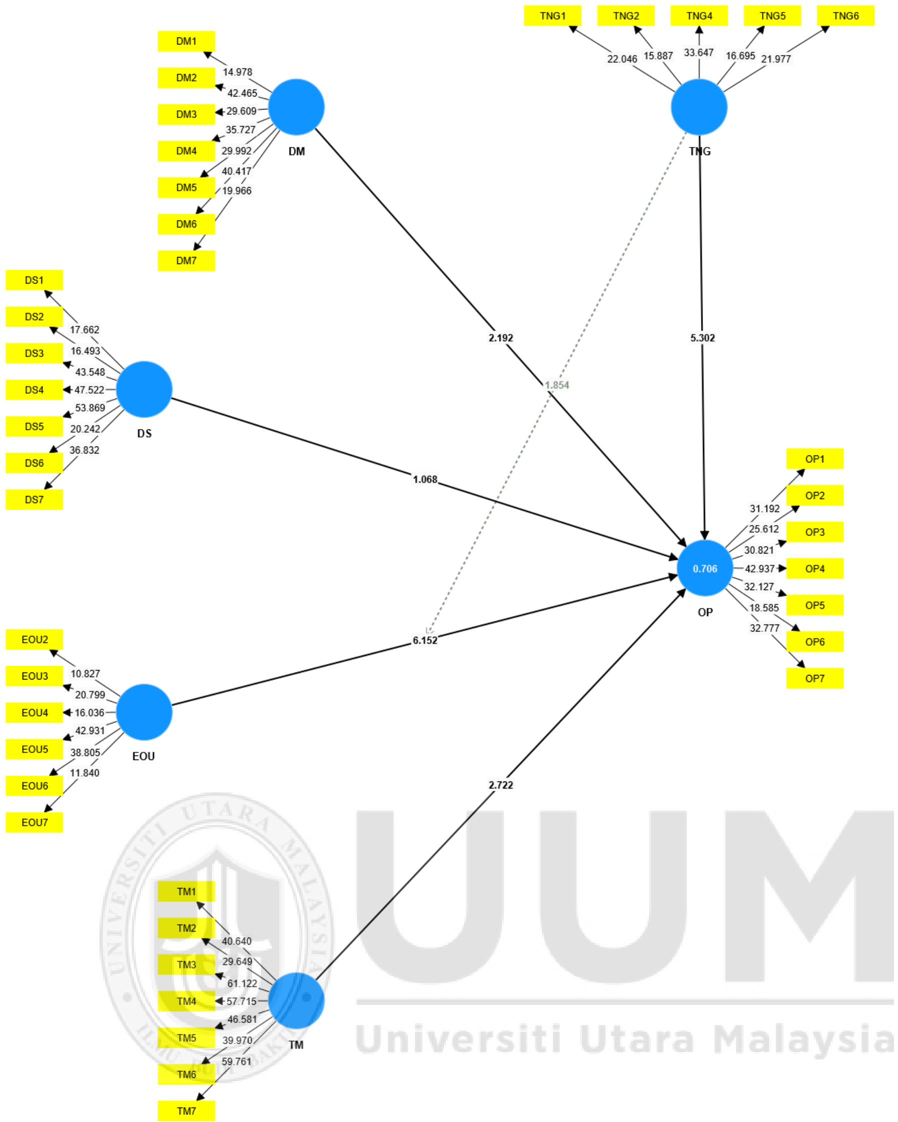

Figure 4.12
Model of Moderating Effect of Training between Ease of Use and Organizational Performance

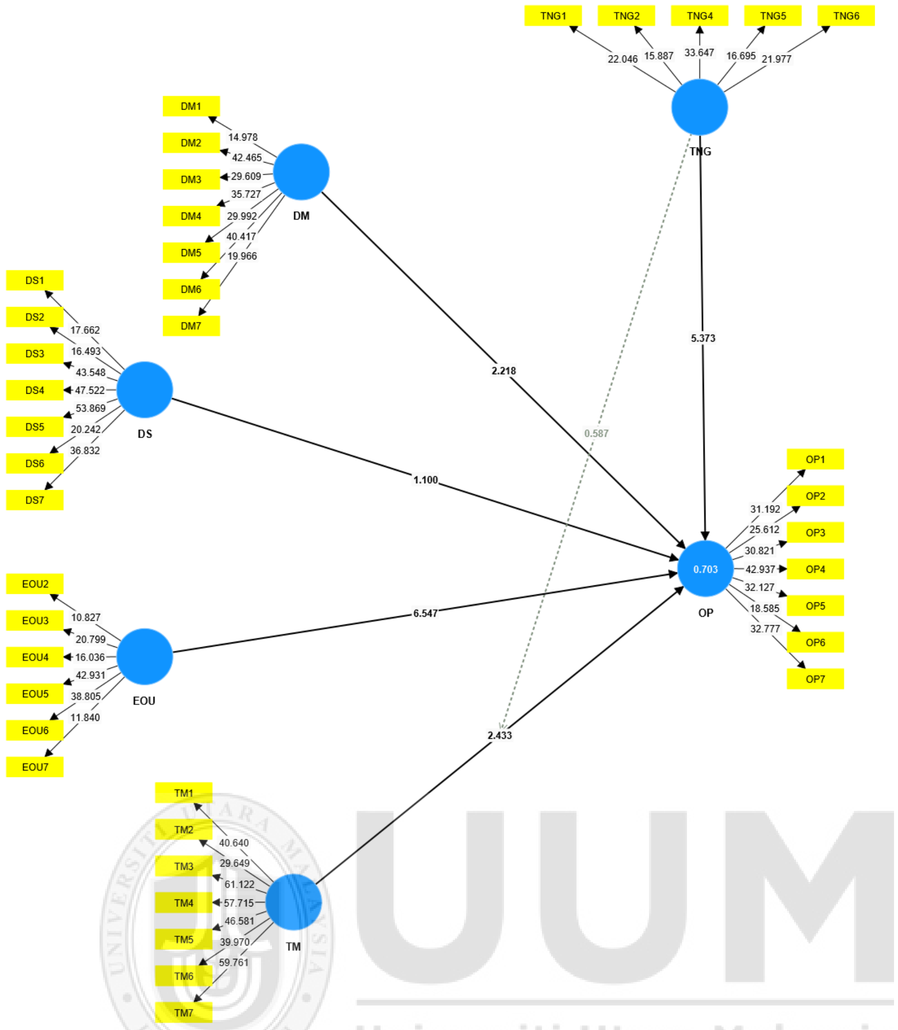

Figure 4.13
Model of Moderating Effect of Training between Top Management Support and Organizational Performance

Table 4.14
Structural Model Assessment with Moderator

Hypothesis	**Relationship**	**Standard Beta**	**T statistics**	**P values**	**Decision**
H5(a)	(TNG) -> (DM) -> (OP)	-0.065	1.379	0.084	Not Supported
H5(b)	(TNG) -> (DS) -> (OP)	-0.036	1.221	0.111	Not Supported
H5(c)	(TNG) -> (EOU) ->(OP)	-0.05	1.854	0.032	Supported
H5(d)	(TNG) -> (TM) -> (OP)	-0.023	0.587	0.279	Not Supported

Note: *p < 0.05 (T Statistics> 1.645) for 1-tailed test. DM=Data quality management, DS=Data Security, EOU=Ease of Use, OP=Organizational Performance, TM=Top Management Support, TNG=Training.

From Table 4.14, the results showed that the moderating effect of training between data quality management and organizational performance (β=-0.065, t=1.379, p=0.084) has no positive relationship. Hence, Hypothesis 5(a) was not supported. Similarly, the moderating effect of training between data security and organizational performance (β=-0.036, t=1.221, p=0.111) has no positive relationship. Hence, Hypothesis 5(b) was not accepted. In contrary for moderating effect of training between ease of use and organizational performance (β=-0.05, t=1.854, p=0.032) has a positive relationship. Hence, Hypothesis 5(c) was accepted. Finally, the moderating effect of training between top management support and organizational performance (β=-0.023, t=0.587, p=0.279) has no positive relationship. Therefore, Hypothesis 5(d) was not accepted. Overall, the result shows that hypothesis 5(c); ease of use is the only one that has positive relationship.

4.8.3 Slope Analysis

Training (TNG) x Data Quality Management (DM)

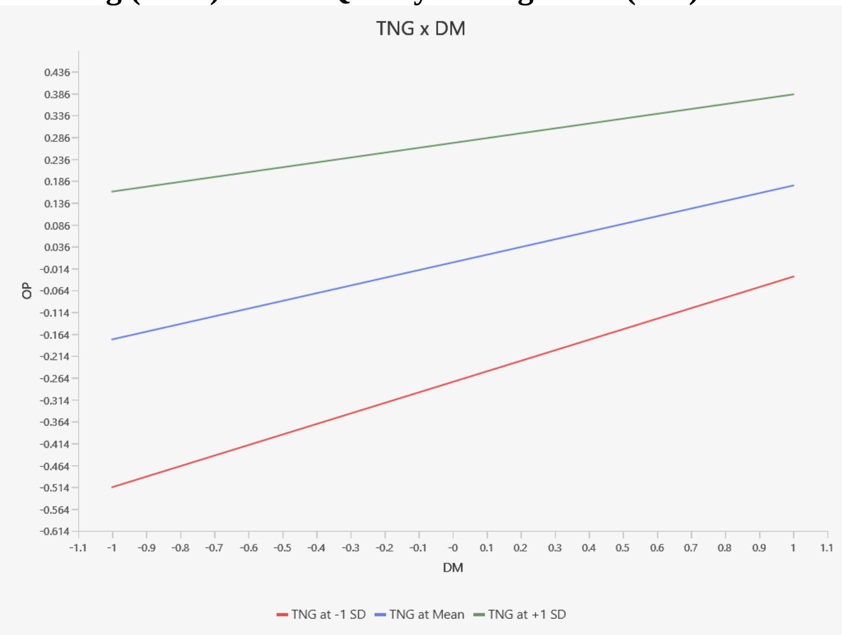

Figure 4.14
Training (TNG) x Data Quality Management (DM)

The result for TNG (training) and DM (Data Quality Management) with the t-test value of 1.379 and p-value of 0.084 indicate no positive relationship with OP (Organizational Performance). As indicated in Table 4.16, the effect size for this interaction is small (f-squared=0.035). However, the slopes for TNG at -1 SD (red line) shows a steeper line than the other 2 lines (TNG at mean, TNG at +1 SD). This could be derived as individuals with lower levels of training see a greater improvement in Organizational Performance (OP) with Data Quality Management (DM) enhancements than those with average or higher levels of training. This is supported by the assumption that persons with less beginning training may struggle more with data quality management, therefore any increase in Data quality management techniques might result in proportionally larger gains in performance.

Training (TNG) x Data Security (DS)

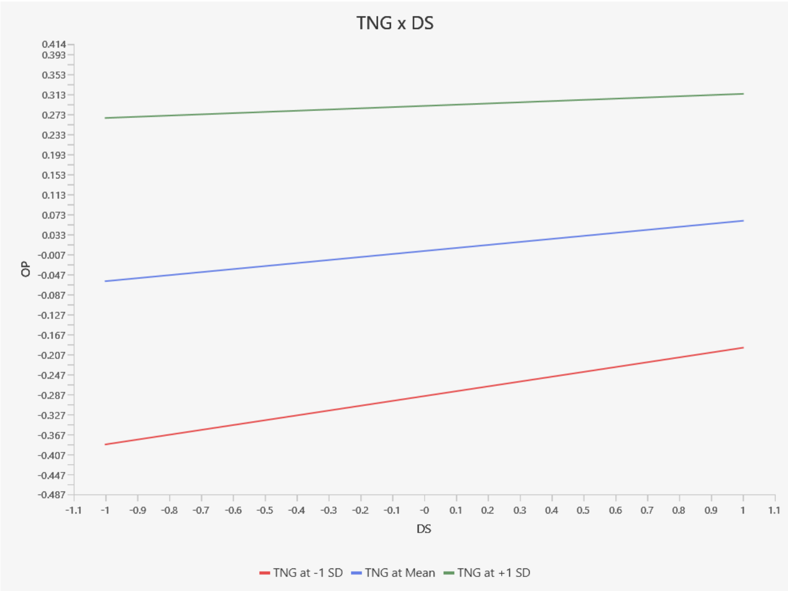

Figure 4.15
Training (TNG) x Data Security (DS)

The result for TNG (training) and DS (Data Security) with the t-test value of 1.221 and p-value of 0.111 indicate no positive relationship with OP (Organizational Performance). As indicated in Table 4.16, the effect size for this interaction is small (f-squared=0.012), even smaller than effect size of TNG * DM. The slopes show gradual incremental for TNG at -1 SD (red line) shows a steeper line than the other 2 lines (TNG at mean, TNG at +1 SD). This could be derived as individuals with lower levels of training see a greater improvement in Organizational Performance (OP) with Data Security (DS) enhancements than those with average or higher levels of training. This is supported by the assumption that persons with less beginning training may struggle more with data security, therefore any increase in Data Security controls might result in proportionally larger gains in performance. This can be contributed to the situation whereby those with less initial training may struggle more with data security, hence improvements in DS result in correspondingly greater advances in performance.

Training (TNG) x End of Use (EOU)

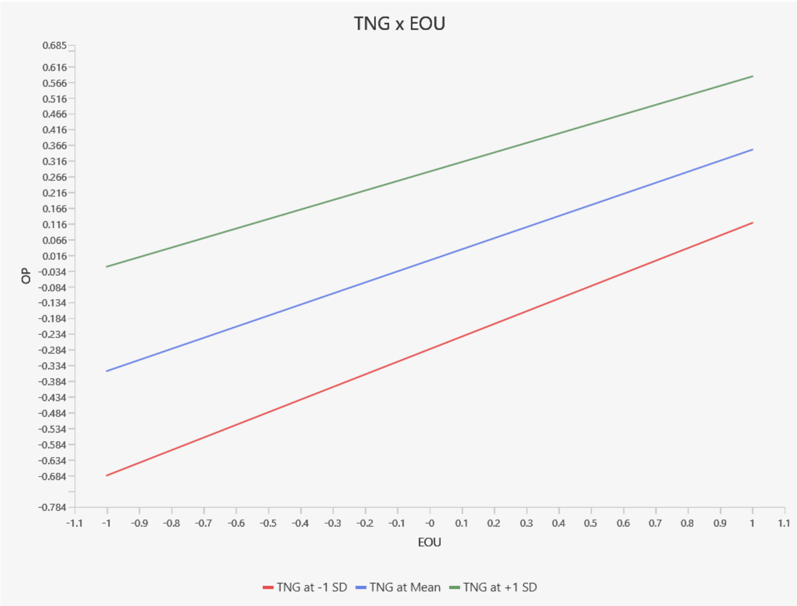

Figure 4.16
Training (TNG) x End of Use (EOU)

The result for TNG (training) and EOU (End of Use) with the t-test value of 1.854 and p-value of 0.032 indicate no positive relationship with OP (Organizational Performance). As indicated in Table 4.16, the effect size for this interaction is moderate (f-squared=0.21). The slopes show consistent incremental growth between the three slope lines (TNG at -1 SD, TNG at mean, TNG at +1 SD) that indicates that support from End of Use positively impacts performance. There is an obvious steep for TNG at -1 SD (red line) compared to the others. The steeper slope of the red line (TNG at -1 SD) emphasizes the crucial role of ease of use in increasing organizational performance, particularly for individuals with less starting training experience. As noted by Alzahrani & Seth (2021), Fosso Wamba et al. (2019) and Grover et al. (2018), organizations that focus on making technology more accessible and user–friendly experience can significantly improve performance benefits to the organizations. This approach involves strong commitment from the individuals and good support of Big Data technologies especially in relation to user experience design.

Training (TNG) x Top Management Support (TM)

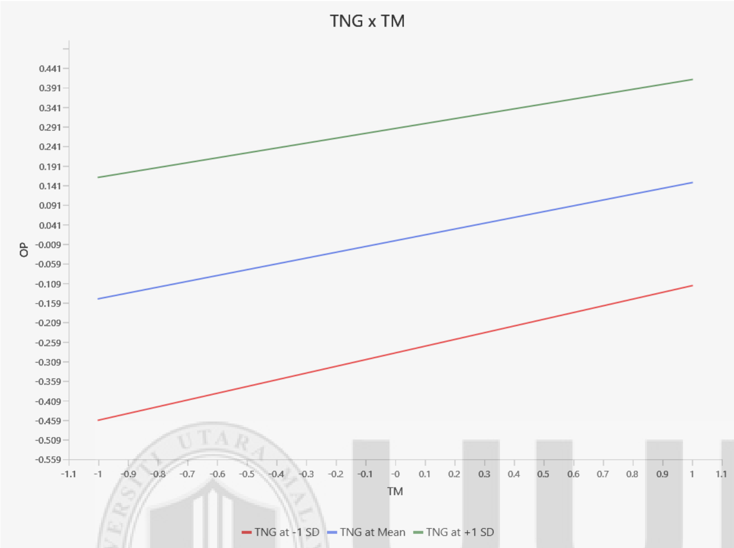

Figure 4.17
Training (TNG) x Top Management Support (TM)

The result for TNG (training) and TM (Top Management) with the t-test value of 0.587 and p-value of 0.279 indicate no positive relationship with OP (Organizational Performance). As indicated in Table 4.16, the effect size for this interaction is small (f-squared=0.032). The slopes show consistent incremental growth between the three slope lines (TNG at -1 SD, TNG at mean, TNG at +1 SD) that indicates that support from top management positively impacts performance. There is a slight steep for TNG at -1 SD (red line) compared to the others. This can be translated where individuals with a lower level of training experience more performance gains from increased top management support. Overall, this emphasizes the crucial importance of top management in improving organizational performance, even for individuals with less expertise.

4.9 The Predictive Relevance of the Model

4.9.1 Coefficient of Determination (R^2)

R-squared (R^2) is a statistical measure that quantifies the proportion of variation explained by an independent variable in a regression model for a dependent variable. The strength of the relationship between the research model and the dependent variable is measured by R-squared. To enable a thorough examination of the model's predictive relevance, Hair (2021) developed next-generation prediction metrics for composite-based PLS-SEM, which allowed for a more in-depth understanding of the model's predictive ability. Table 4.15 illustrates the strength of the model. The R-squared of the variables, namely data quality management, data security, ease of use, top management support is found to be 0.710. Thus, it shows that model used in this study was substantial as suggested by Chin W (1998). It also implies that the model is a better fit.

Table 4.15
Strength of the Model (R^2)

Constructs	**R-square**
Data Quality Management * Training → Organizational Performance	0.71
Data Security * Training → Organizational Performance	
Ease of Use * Training → Organizational Performance	
Top Management Support * Training → Organizational Performance	

4.9.2 Effect Size (F^2)

Effect size is a metric for determining the magnitude of an effect that is independent of the sample size. Table 4.16 shows that the effect size for data quality management of 0.035 implying the moderating effect was small, data security of 0.012 implying the moderating effect was small, ease of use of 0.210 implying the moderating effect was moderate, top management support of 0.032 implying the moderating effect was small, as suggested by Cohen (1988). Moderating effect sizes (f^2) values of 0.02 is considered small, 0.15 is moderate and above 0.35 is considered strong (Cohen, 1988).

Table 4.16
Effect Size (F^2*)*

Construct	f-squared	Effect Size	T test	p-values
DM * TNG → OP	0.035	Small	1.379	0.084
DS * TNG → OP	0.012	Small	1.221	0.111
EOU * TNG → OP	0.210	Moderate	1.854	0.032
TM * TNG → OP	0.032	Small	0.587	0.279

Note: DM=Data quality management, DS=Data Security, EOU=Ease of Use, OP=Organizational Performance, TM=Top Management Support, TNG=Training.

Based on this analysis, f-squared effect size analysis shows that different variables have different effects on organizational performance. Data quality management showed a small effect size (f-squared=0.035), indicating that approximately 3.5% of the variation in organizational performance can be attributed to this factor. Similarly, the effect size of data security was relatively small (f-squared=0.012), indicating a smaller impact on organizational performance, accounting for approximately 1.2% of the variability. In contrast, Ease of Use had a moderate effect size (f-squared=0.210), meaning that approximately 21% of the variance in organizational performance. Finally, top management support had a small effect size (f-squared=0.032), indicating that it accounted for approximately 3.2% of the variability in organizational performance. The overall findings indicate the importance of various factors influencing the impact towards organizational performance, with particularly emphasize larger effect size on Ease of Use.

4.9.3 Predictive Relevance (Q^2)

The model's predictive relevance (Q^2), is examined using a 7-distance blindfolding process (Hair et al., 2017). The Q^2 value was derived using SmartPLS 4's blindfolding technique, which systematically omits and predicts sections of the data matrix to measure the model's predictive power (Hair et al., 2017). A value of Q^2 larger than 0 indicates the model's predictive usefulness for the stated endogenous construct, that the Organizational Performance model has a Q^2 value of 0.45, suggesting its good predictive usefulness.

Q^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large predictive importance for an endogenous variable (Sarstedt et al., 2017; Chin, 1998. This guarantees that the model not only matches the sample data, but also has the ability to reliably forecast additional data points. Table 4.17 shows the predictive relevance (Q^2) of this investigation.

Table 4.17
Predictive Relevance (Q^2)

Predictive Relevance Q^2	Q^2 (=1-SSE/SSO)
Organizational Performance	0.45

4.10 Summary of Hypothesis Testing

This section summarizes the results of both the inner model assessment and the analysis of training's moderating effect on the relationship between Big Data adoption determinants and organizational performance. Partial Least Squares Structural

Equation modeling (PLS-SEM) was employed to assess the direct effects of data quality management, data security, ease of use, and top management support on organizational performance, as well as the moderating effect of training on these relationships.

The inner model assessment revealed that three of four direct relationships were supported. Data quality management, ease of use, and top management support had a positive and significant impact on organizational performance, demonstrating that these factors are critical for improving organizational outcomes when adopting Big Data. However, data security had no significant impact on organizational performance, implying that other contextual factors may influence its efficacy.

According to the moderating effect study, training only boosts the influence of ease of use on organizational performance, but has no significant moderating effect on the links between data quality management, data security, or top management support and organizational performance. This conclusion shows that training may be more effective in improving user-friendly technologies or processes, whilst other factors require different interventions to influence performance outcomes. Table 4.18 presents a summary of the findings, and conclusions for all hypotheses.

Table 4.18
Results of Hypotheses Testing for Direct and Moderating Effects

Hypothesis	**Relationship**	**Standard Beta**	**T statistics**	**p-values**	**Decision**
H1	DM → OP	0.17	2.19	0.029	Supported
H2	DS → (OP)	0.063	1.066	0.286	Not Supported
H3	EOU → OP	0.359	6.391	0.000	Supported
H4	TM → OP	0.150	2.483	0.013	Supported
H5(a)	TNG → DM → OP	-0.065	1.379	0.084	Not Supported

H5(b)	TNG → DS → OP	-0.036	1.221	0.111	Not Supported
H5(c)	TNG → EOU → OP	-0.05	1.854	0.032	Supported
H5(d)	TNG → TM → OP	-0.023	0.587	0.279	Not Supported

Note: DM=Data quality management, DS=Data Security, EOU=Ease of Use, OP=Organizational Performance, TM=Top Management Support, TNG=Training.

e) **H1**: There is positive significance between data quality management in Big Data adoption and organizational performance. (β=0.17, T=2.19, p-value=0.029).

f) **H2**: There is no positive significance between data security in Big Data adoption and organizational performance. (β=0.063, T=1.066, p-value=0.286).

g) **H3**: There is positive significance between ease of use in Big Data adoption and organizational performance. (β=0.359, T=6.391, p-value=0.000).

h) **H4**: There is positive significance between top management support in Big Data adoption and organizational performance. (β=0.15, T=2.483, p-value=0.013).

i) **H5(a)**: There is no positive significance of training in Big Data adoption moderating the relationship between data quality management and organizational performance (β=-0.065, T=1.379, p-value=0.084).

j) **H5(b)**: There is no positive significance of training in Big Data adoption moderating the relationship between data security in Big Data adoption and organizational performance (β=-0.036, T=1.221, p-value=0.111).

k) **H5(c)**: There is positive significance of training in Big Data adoption moderating the relationship between ease of use in Big Data adoption and organizational performance (β=-0.05, T=1.854, p-value=0.032).

l) **H5(d)**: There is no positive significance of training in Big Data adoption moderating the relationship between top management support in Big Data adoption and organizational performance (β=-0.023, T=0.587, p-value=0.279).

4.11 Summary

This chapter systematically presented and discussed all of the findings from the data analysis conducted with SmartPLS software. The findings demonstrated that data quality management, ease of use, and top management support had a substantial impact on organizational performance in the context of Big Data Adoption. However, data security did not have a substantial impact. Furthermore, the study found that training considerably moderates the relationship between ease of use and organizational performance. Overall, these findings shed light on how companies may strategically improve performance through targeted training and better management of Big Data adoption factors.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Introduction

This chapter reviews the study findings in relation to the research objectives, questionnaire results, and conclusions developed in earlier chapter. It discusses the theoretical and practical implications of the research findings. Additionally, it highlights the study's contributions, limitations, and future research directions.

5.2 Recapitulations of Study

This section presents the conclusion and discussion of the findings about the research objectives established at the beginning of the study. This research primarily aimed to investigate the impact of data quality management, data security, ease of use, and top management support on organizational performance, particularly emphasizing the moderating effect of training. This study employed the Technology-Organization-Environment (TOE) framework and Resource-Based View (RBV) theory to address the gap in comprehending how training can enhance the influence of these factors in Malaysian Digital Status companies within the Global Business Services (GBS) sector.

Based on the eight hypotheses tested, four received empirical support. The findings reveal that data quality management, ease of use, and top management support significantly influence organizational performance, while data security showed no significant effect. The findings reveal that data quality management, ease of use, and top management support significantly influence organizational performance, however data security shown no significant effect. Furthermore, training notably influenced the association between ease of use and organizational performance, although it did not affect the relationships between data quality management, data security, or top management support and organizational performance.

This chapter will elaborate on these insights, emphasizing both theoretical and practical contributions. The subsequent section will examine the study's limitations, establishing a basis for future research directions.

This study examines determinants contribution to Organizational Performance on Data Quality Management, Data Security, Ease of Use, Top Management Support factors among Malaysia digital status companies. The aim of this study is to achieve research objective stated below:

a) To examine the relationship between data quality management and organizational performance.
b) To examine the relationship between data security and organizational performance.
c) To examine the relationship between ease of use and organizational performance.
d) To examine the relationship between top management support and organizational performance.
e) To examine whether training moderates the relationship between determinants and organizational performance.
    i. To examine whether training moderates the relationship between data quality management and organizational performance.
    ii. To examine whether training moderates the relationship between data security

and organizational performance.

iii. To examine whether training moderates the relationship between ease of use and organizational performance.

iv. To examine whether training moderates the relationship between top management support and organizational performance.

In testing the hypotheses, SEM was applied to investigate the relationships between determinant contributions and organizational performance on Big Data adoption.

Table 5.1
Summary of the Results for Training as Moderating variable

Hypothesis	**Relationship**	**Standard Beta**	**T statistics**	**P values**	**Decision**
H1	(DM) → (OP)	0.170	2.190	0.029	Supported
H2	(DS) → (OP)	0.063	1.066	0.286	Not Supported
H3	(EOU) → (OP)	0.359	6.391	0.000	Supported
H4	(TM) → (OP)	0.150	2.483	0.013	Supported
H5(a)	(TNG) -> (DM) -> (OP)	-0.065	1.379	0.084	Not Supported
H5(b)	(TNG) -> (DS) -> (OP)	-0.036	1.221	0.111	Not Supported
H5(c)	(TNG) -> (EOU) ->(OP)	-0.050	1.854	0.032	Supported
H5(d)	(TNG) -> (TM) -> (OP)	-0.023	0.587	0.279	Not Supported

Note: DM=Data quality management, DS=Data Security, EOU=Ease of Use, OP=Organizational Performance, TM=Top Management Support, TNG=Training.

5.3 Discussion of Study Findings

This study aims to understand why and how certain determinants contribute to organizational performance. In this study, all hypotheses were accepted except for the hypothesis related to data security. The results showed that the determinants of data quality management, ease of use, and top management support indicate a positive relationship with organizational performance, while data security demonstrated no significant relationship. Furthermore, the study confirmed that training, which acts as a moderator, strengthens the relationship between ease of use and organizational performance, but not the relationships involving the other determinants.

Notably, the determinant contributions examined in this study are grounded in the existing literature, particularly the Technology-Organization-Environment (TOE) framework and the Resource-Based View (RBV), which serve as the underpinning theories. These theories help explain how the determinants interact to achieve organizational performance, with training acting as a moderating variable in the form of an upskilling dimension. A total of eight hypotheses were developed and tested. To meet the objectives of this study, four hypotheses were tested for direct effects, and another four tested the moderating effects of training. Out of these, four hypotheses (H1, H3, H4, H5(c)) were empirically supported.

5.3.1 Data Quality Management and Organizational Performance

To achieve the first objective of this study regarding the effect of Data quality management on the use of Big Data towards organizational performance for Malaysia Digital Status companies, the relationship between data quality management and organizational performance was examined. Based on the result shown in Table 5.1, data quality management and organizational performance have positive relationship and significant at 0.05 level of significant whereby it supported hypothesis H1 (β=0.170, t=2.19, $p<0.05$). This finding aligns with prior research, which highlights the critical role of data quality in improving organizational performances (Janssen et al., 2017; Dias et al., 2021; Wook et al., 2021; Shanmugam et al., 2023; Al-madhrahi et al., 2022).

This study emphasizes that robust data quality management comprising completeness, accuracy, and consistency; positively contributes to organizational performance. This study confirms the findings of (Peltier et al., 2013 ; Janssen et al., 2017 ; Dias et al., 2021), indicating that organizations that maintain high data quality in technological infrastructure, organizational practices, and environmental compliance can augment decision-making capabilities, stimulate innovation, and enhance overall performance. This conclusion is further supported by Kalra (2020), who highlighted that organizations' propensity to invest in Big Data solutions is significantly affected by their assessment of the data quality they handle.

Companies with inadequate data quality have significant challenges in the adoption and implementation of Big Data efforts. Parker & Parker, (2023) contended that insufficient data quality diminishes confidence in data analytics results, thereby preventing companies from supporting Big Data initiatives. This aligns with the findings of (Khong et al., 2023), who emphasized the importance of high-quality data for informed decision-making that directly influences organizational performance. This study enriches the conversation on the complexity of data quality management, often associated with the attributes of Big Data: volume, velocity, and variety. Studies by (Onyeabor & Ta'a, 2018; Shanmugam et al., 2023; Wook et al., 2021) have emphasized the difficulties associated with managing incomplete, inaccurate, and inconsistent data. The aforementioned problems highlight the necessity of maintaining high-quality data, as flaws and inconsistencies can severely impede operational efficiency, as indicated by (Al-madhrahi et al., 2022; Dias, 2021).

Enhancing data quality management enables companies to avoid the limitations of inadequate data quality while reaping the advantages of data-driven decision-making, such as increased operational efficiency, decreased costs, and heightened competitiveness. This reinforces the idea that data quality management is a crucial factor influencing organizational success regarding Big Data adoption, as articulated by Al-Salim et al. (2022) and Nilashi et al. (2023).

This study's findings strongly indicate that data quality management significantly enhances organizational performance, which echoes the conclusions of several key studies in the field. This highlights the importance of continuous investments in data quality practices to maximize the benefits of Big Data initiatives in Malaysia's Digital Status companies.

5.3.2 Data Security and Organizational Performance

The second objective of this study regarding the effect of Data Security on the use of Big Data towards organizational performance for Malaysia Digital Status companies, the relationship between Data Security and organizational performance was examined. Based on the result shown in Table 5.1, the relationship between Data Security and organizational performance was found to be negative and does not influence between Data Security and organizational performance. The significant at the level of p value of significant is more than 0.05, therefore, not supporting hypothesis H2 (β=0.063, t=1.066, p>0.05). This study is consistent with the result by the study conducted by

Ghasemaghaei (2020) that supported data security is not critical factor for Big Data adoption.

This finding aligns with several previous studies that suggest while data security is an important consideration, it does not always act as a critical determinant for the adoption of Big Data technology (Yadegaridehkordi et al., 2018; Haddad et al., 2019; Ghasemaghaei, 2020; Nilashi et al., 2023; Nasrollahi et al., 2021). Companies are increasingly adopting Big Data solutions because the potential benefits such as enhanced decision-making, operational improvements, and gaining competitive advantage, outweigh concerns related to privacy and security breaches (Lutfi, Al-Khasawneh, et al., 2022).

For companies with stringent regulatory frameworks like healthcare, the adoption of Big Data continues despite inherent security risks. As noted by (Dias, 2021), the benefits of analyzing large datasets, such as clinical or financial data, to improve operational efficiency and optimize resource allocation, are seen as more valuable than the risks posed by data security concerns. Similarly, Dias, (2021) and Ghaleb et al. (2021), emphasized that the strategic benefits of using Big Data encourage its adoption, even when there are security challenges.

The findings of this study are consistent with research indicating that data security, while important, does not necessarily impede the adoption or performance outcomes associated with Big Data analytics. For example, studies like Yadegaridehkordi et al. (2018) and Lutfi, Al-Khasawneh, et al. (2022) have shown that security concerns often rank behind other risk factors such as perceived benefits or customer satisfaction in motivating organizations to adopt Big Data.

This study contributes to the existing body of knowledge by reinforcing the concept that while data security remains a significant consideration, it is not always a decisive factor in determining organizational performance improvements through Big Data adoption. Instead, organizations are willing to accept the associated risks to capitalize on the broader advantages that Big Data offers, such as efficiency gains and competitive edge.

5.3.3 Ease of Use and Organizational Performance

The third objective of this study regarding the effect of ease of use on the use of Big Data towards organizational performance for Malaysia Digital Status companies, the relationship between ease of use and organizational performance was examined. Based on the result shown in Table 5.1, the relationship between Ease of Use and organizational performance was found to be positive and significant at the level of 0.05 of significant, therefore, supporting hypothesis H3 ($\beta=0.359$, $t=6.391$, $p<0.05$) as per previous result conducted by (Asiri et al., 2024; El-Haddadeh et al., 2021; Ghaleb et al., 2021; Haddad et al., 2019; Teoh et al., 2021)

As these studies have shown, ease of use is critical in influencing the amount to which companies adopt and use Big Data solutions. Teoh et al. (2021) underlined that companies are more likely to use Big Data solutions that are user-friendly and straightforward, as this lowers technical hurdles and speeds up integration into daily operations. The simplicity with which employees may use Big Data tools boosts operational efficiency, customer insights, and overall performance.

Furthermore, studies conducted by Haddad et al. (2019) and Ghaleb et al. (2021) discovered that ease of use is often constrained by resource limitations; therefore, implementing user-friendly technology reduces training costs and increases the likelihood of successful adoption

The outcomes of this study are consistent with previous research, suggesting that the more user-friendly Big Data technologies are regarded to be, the more likely they are to be adopted, resulting in greater organizational performance. This is especially important for Malaysian Digital Status organizations, where ease of use heavily influences their decision to incorporate Big Data technologies into their operations.

This study adds to the expanding body of evidence by demonstrating the strong positive relationship between ease of use and organizational effectiveness. It emphasizes that businesses prioritize the use of Big Data technologies that are simple to use and administer, guaranteeing that the benefits of Big Data, such as operational efficiency and decision-making, are crucial without requiring substantial technical knowledge (Grover et al., 2018; Lutfi, Al-Khasawneh, et al., 2022; Fosso Wamba et al., 2019). Companies may get the most out of Big Data adoption by streamlining the user experience.

5.3.4 Top Management Support and Organizational Performance

Next objective of this study regarding the effect of Top Management Support on the use of Big Data towards organizational performance for Malaysia Digital Status companies, the relationship between Top Management Support and organizational performance was examined. Based on the result shown in Table 5.1, the relationship between Top Management support and organizational performance was found to be positive and significant at the level of 0.05 of significant, therefore, supporting hypothesis H4 ($\beta=0.15$, $t=2.483$, $p<0.05$) as per previous result conducted by Al-Rahmi Haddad et al. (2019), Ghaleb et al. (2021), Alyoussef and Al-Rahmi (2022), Falahat et al. (2023), and Asiri et al. (2024).

Top management support is required to ensure that Big Data initiatives are aligned with organizational strategy and that sufficient resources are committed for successful implementation. Asiri et al. (2024) found that businesses with senior leadership that promotes data-driven strategies have better data use and performance outcomes. Leaders play a critical role in inspiring staff at all levels to embrace Big Data technology by promoting data-driven decision-making and emphasizing the importance of analytics-derived insights.

Furthermore, (Haddad et al., 2019) and (Falahat et al., 2023) emphasize that top management not only provides the necessary resources, but also develops an innovative culture, which is critical for effective Big Data implementation. Their assistance aids in overcoming opposition to change, aligning Big Data efforts with long-term goals, and creating an atmosphere in which data-driven insights are emphasized.

Furthermore, Ghaleb et al. (2021) stated that senior leadership involvement is critical for keeping the company focused on strategic initiatives like Big Data even as commercial objectives vary. This is especially critical in situations with frequent change, as ongoing leadership support ensures that Big Data initiatives are integrated into the organization's overall goals.

This study's findings are consistent with previous research, indicating that top management support is a critical factor of successful Big Data adoption and organizational performance. Senior leadership's commitment to promoting data-driven strategies and allocating resources is critical for realizing the full potential of Big Data technology. Leaders can improve organizational performance by creating a supportive climate that promotes data utilization and creativity.

5.3.5 Moderating Effect of Training between Data Quality Management with Organizational Performance

Based on the results presented in Table 5.1, moderating effect of training had a direct negative effect with data quality management and organizational performance (β=-0.065, t=1.379, p>0.5). The analysis carried out using PLS Path Modelling techniques showed that training as a moderating variable had a negative and statistically insignificant effect on the relationship between Data quality management and organizational performance. This result aligns with previous studies conducted by (Dubey et al., 2019; Su et al., 2022 ; Côrte-Real et al., 2020; Nilashi et al., 2023; Peltier et al., 2013; Wook et al., 2021; Yadegaridehkordi et al., 2018).

Despite the significant positive direct relationship between data quality management and organizational performance (H1 supported), the moderating role of training (H5a) was not supported. This finding suggests that while effective data management remains important for improving organizational performance, training does not significantly enhance or modify this relationship in the context of Big Data adoption.

The supported relationship between data quality management and organizational performance demonstrates that increased data quality benefits organizations by improving operational efficiency and decision-making processes. However, the expectation that training would function as a significant moderator was not supported, implying that, while training is important, it does not always change the impact of data quality management on performance in this setting.

Despite expectations that training would mitigate the association between data quality management and organizational performance, the findings indicate that data quality has a larger and more direct impact on performance. This implies that, while training may increase employees' capacity to use data tools, it does not significantly improve performance results based on data quality. This could be due to the structure of the training programs, which may not be well-suited to properly address the intricacies of Big Data technology in these organizations.

The findings are consistent with previous research that emphasizes the relevance of data quality in boosting organizational performance Nilashi et al., 2023; Peltier et al., 2013; Ghasemaghaei & Calic, 2019). However, the lack of support for training as a moderator is consistent with previous research, which revealed that inadequate or outdated training programs could have a limited impact on performance outcomes (Mahmood et al., 2023; Akter et al., 2016). This shows that these training programs may not be adequately tailored to maximize the benefits of data quality management.

Previous study, such as that conducted by Ahmad et al. (2023), has shown that training is crucial in enhancing the perceived usefulness and ease of use of technology, which in turn improves performance. However, the current study's findings contradict this, demonstrating that training does not significantly alter the association between data quality management and organizational performance. This variability could be attributed to variances in how training programs are implemented or perceived across industries or organizational environments.

In practice, these findings indicate that organizations should continue to spend in training to ensure that staff are conversant with Big Data tools, but they should also emphasize the development and maintenance of high-quality data management systems. Companies may need to reevaluate their training programs to ensure that they are not only comprehensive, but also directly related to enhancing data quality management processes.

From a practical view, these results suggest that while organizations should continue to invest in training to ensure employees are familiar with Big Data tools, they should also prioritize the development and maintenance of high-quality data management systems. Companies may need to reassess their training programs to ensure the content of the training should also educate the importance of improving data quality management processes. For example, companies that particularly be facing resource constraints, a focus on improving data quality may yield more immediate performance benefits than investing heavily in training programs that may not have a direct impact.

5.3.6 Moderating Effect of Training between Data Security with Organizational Performance

Based on the results presented in Table 5.1, moderating effect of training had a negative effect with Data Security and Organizational Performance (β=-0.036, t=1.221, p>0.5). The analysis carried out using PLS Path Modelling techniques showed that training as a moderating variable had a negative and statistically insignificant effect on the relationship between Data Security and the organizational performance. This result aligns with previous studies conducted by Maroufkhani et al. (2019), Mahdi Nasrollahi and Javaneh Ramezani (2021), and Lutfi et al. (2022).

Although data security did not show a significant direct relationship with organizational performance (H2 not supported), the moderating role of training (H5b) was likewise not supported. This indicates that training does not play a critical role in strengthening the relationship between data security and organizational performance. This suggests that training does not enhance or weaken the relationship between data security and organizational performance in the context of Malaysia Digital Status companies. This outcome aligns with prior research by Maroufkhani et al. (2019), Nasrollahi & Ramezani (2021), and Lutfi et al. (2022), which also found limited or no significant moderating effect of training in various technology adoption scenarios.

These findings challenge the common expectation that training plays a pivotal role in bridging gaps in data security implementation and its influence on organizational performance. While training is widely regarded as essential for equipping employees with the skills needed to manage data security effectively, the results suggest that training programs in the studied organizations may not be sufficiently aligned with the specific security challenges faced by these companies. Factor for this misalignment is that training may lag behind the rapid evolution of security threats, making it difficult for employees to apply the knowledge effectively in real-time situations (Maroufkhani et al., 2019).

This finding is consistent with the arguments in previous studies, where it was highlighted that although data security is critical for protecting sensitive information and maintaining regulatory compliance, its influence on organizational performance is often influence by other factors, such as the external environment, organizational priorities, and resource allocation (Anawar et al., 2022). In addition to this, past studies highlighted that while training can improve awareness and technical skills, it may not necessarily result in significant improvements in performance unless supported by a broader organizational culture that prioritizes data security as a strategic issue (Maroufkhani et al., 2019; Nasrollahi et al., 2021).

Interestingly, while some studies have shown a positive relationship between data security training and organizational performance (Salleh & Janczewski, 2019; Alzahrani & Seth, 2021), these findings contribute to the growing body of research that questions the universal efficacy of training programs. For instance, in environments where operational efficiency is prioritized over stringent data security practices, training might not yield the desired performance improvements (M. T. Huynh et al., 2023). This discrepancy points to the need for further investigation into the specific contexts in which training can enhance security-related outcomes.

From a practical perspective, these findings highlight the importance of tailoring training programs to the specific security needs of the organization. Companies must ensure that their training initiatives are continuously updated to address the latest security threats and integrate seamlessly with their overall data management strategies. Furthermore, management must recognize that training alone may not be enough to secure performance gains. A more holistic approach that combines training with strategic initiatives such as fostering a security-conscious organizational culture and aligning security with operational goals may be required to achieve meaningful improvements in performance.

5.3.7 Moderating Effect of Training between Ease of Use with Organizational Performance

Based on the results presented in Table 5.1, moderating effect of training had a positive effect with Ease of Use and organizational performance (β=-0.05, t=1.854, p<0.5). The analysis carried out using PLS Path Modelling techniques showed that training as a moderating variable had a positive and statistically significant effect on the relationship between ease of use and organizational performance.

This finding emphasizes training as a moderating factor between ease of use and organizational performance exhibited a significant positive effect. Despite the strong positive direct relationship between ease of use and organizational performance (H3 supported), the inclusion of training (H5c supported) further enhances this relationship. This finding implies that when ease of use is complemented by training, organizational performance can be further improved, highlighting the importance of user-friendly systems combined with adequate training.

Training is shown to be a key enabler in facilitating ease of use for Big Data technologies. Without proper training, even user-friendly tools may not reach their full potential in enhancing organizational performance. This research highlights that training helps reduce the cognitive effort required to navigate Big Data systems, making the technology more accessible and less daunting to employees. Consequently, as training improves the usability of Big Data tools, organizations experience enhanced operational efficiency, better decision-making, and overall improved performance.

The findings are consistent with previous research. According to Alzahrani & Seth (2021), Fosso Wamba et al. (2019) and Grover et al. (2018), user-friendly interfaces and training are crucial for successful technology adoption. According to Hadidi & Power (2020) and Maroufkhani, Wan Ismail, et al. (2020), proper training improves employees' ability to engage with complicated systems, especially in Big Data analytics environments. The findings support the premise that training increases staff acceptance of technology, leading to improved organizational performance. Training is essential for making Big Data technology more user-friendly. Proper training is essential for even the most user-friendly products to really enhance organizational performance. Training reduces the cognitive work needed to manage Big Data platforms, making the technology more accessible to employees. Training enhances the usability of Big Data technologies, leading to greater operational efficiency, decision-making, and overall performance.

The positive moderation effect suggests that well-structured training programs improve perceived ease of use of Big Data technology, leading to better organizational performance. Ease of use and effective training are key factors in Big Data adoption, leading to improved organizational performance. While previous study has shown that training has a beneficial moderating effect, there is mixed evidence on the effects of ease of use on performance. According to Parulian et al. (2023), improving performance requires tackling fundamental concerns such as data integration and strategic alignment, rather than focusing solely on ease of use. This study suggests that training helps bridge the gap between ease of use and efficient use, particularly for Big Data tools that need advanced management. Training plays a moderating effect in several critical characteristics of organizational performance, including operational efficiency, innovation capacity, and customer experience. Training may help companies optimize workflows, remove operational bottlenecks, and build an environment conducive to innovation. This leads to better decision-making and customer service, resulting in increased production and profitability.

These findings have significant practical implications for companies adopting Big Data technologies. Investing in thorough training programs allows organizations to maximize the potential of user-friendly products and improve adoption processes. Training helps staff gain confidence in using complicated analytical systems, resulting in tangible performance increases. Organizations should develop personalized training programs that cover not only the technical aspects of Big Data technologies, but also integration issues and decision-making processes.

5.3.8 Moderating Effect of Training between Top Management Support with Organizational Performance

Based on the results presented in Table 5.1, moderating effect of training had a negative effect with Top Management support and organizational performance (β=-0.023, t=0.587, p>0.5). The analysis carried out using PLS Path Modelling techniques showed that training as a moderating variable had a negative and statistically insignificant effect on the relationship between Top Management Support and the organizational performance.

Despite the significant positive direct relationship between top management support and organizational performance (H4 supported), the moderating role of training (H5d) was not supported. This finding indicates that while top management support remains crucial for driving organizational performance, training does not significantly alter or enhance this relationship in the context of Big Data adoption.

This finding supports the hypothesis that direct relationship of top management support is positively significant, but it contradicts the expectation that training would improve this relationship. The lack of significant moderation indicates that, while training is important, it may not have a direct impact on how top management support influences performance outcomes in this situation.

The data reveals that training activities may not be properly integrated with top management support techniques for boosting organizational performance. This could be due to a variety of issues, including misalignment of training programs with corporate priorities or senior management's lack of emphasis on continual learning. Training may not have had the necessary influence to temper the top management support-performance link, possibly due to gaps in training content or delivery methods.

These findings are consistent with previous study, which found inconsistency in the role of top management assistance in improving organizational performance (Ijab et al., 2019; Hashim et al., 2021). While top management support is widely recognized as a critical enabler of Big Data adoption (Elbanna & Newman, 2022; Tabesh et al., 2019), some studies have found that its effectiveness can be limited if it is not properly integrated with other organizational factors, such as training (T. N. Huynh et al., 2023). Furthermore, the lack of meaningful moderation by training is consistent with (Grover et al., 2018), who found that training, while required, does not necessarily result in observable performance increases when other strategic elements are in place.

The absence of meaningful moderation by training is consistent with Grover et al. (2018) and G. J. Lee, (2020), who discovered that, while training is important, it does not always result in noticeable performance gains when other strategic elements are present. These studies also found that neither organizational context moderators nor training type had a significant influence on this association. G. J. Lee, (2020) reported that no significant effects of training on business performance whether size or market type in a large-scale international study. These findings imply that the impact of training on organizational performance is more complex and context-dependent than previously thought.

Previous research has revealed contradictory conclusions, emphasizing the complexities of this interaction. For example, several studies have found that top management support without complementary elements such as operational capabilities or strong training programs may have little impact on performance (Alsetoohy et al., 2019; Fareed & Su, 2022). This study contributes to the ongoing debate by indicating that the presence of training does not always improve the performance benefits derived from top management support, possibly due to misaligned training objectives or insufficient follow-through on skill development initiatives (Nasrollahi et al., 2021).

From a practical standpoint, this finding shows that businesses should not rely simply on training to increase the positive impact of top management support on performance. Instead, training programs must be strategically connected with organizational goals and senior management efforts in order to effectively contribute to performance improvement. It also emphasizes the importance of companies critically evaluating their training content, delivery methods, and employee involvement to ensure that training is both relevant and actionable. Furthermore, top management should aggressively promote a learning culture that values continuous skill development.

In terms of specific organizational performance dimensions, such as operational efficiency, innovation, and customer experience, the findings show that, while top management support is beneficial in these areas, training does not have a substantial impact on improving this effect. This shows that, even with strong leadership support, performance improvements may be obtained more through strategic alignment and resource allocation than through training alone. For example, operational improvements may result from leadership-driven efforts, whereas innovation may necessitate more than just training, such as cultivating a creative work atmosphere or offering incentives for experimenting.

5.4 Contributions of the Study

The contributions of this study are discussed based on two perspectives; theoretical contributions and practical contributions.

5.4.1 Theoretical Contributions

This study contributes significantly to the growing body of knowledge on Big Data adoption by combining the Technology-Organization-Environment (TOE) framework with the Resource-Based View (RBV) theory to investigate the impact of Big Data determinants on organizational performance in Malaysian Digital Status companies. This combined theoretical approach is relatively unique, and has not been widely applied before to the existing Big Data adoption research, where most studies typically employ either the TOE or RBV frameworks in isolation (Lutfi, Al-Khasawneh, et al., 2022).

This study makes a unique contribution by combining the TOE and RBV theories to create an integrated framework that investigate how key determinants such as data quality management, data security, ease of use, and top management support, as well as training as a moderator, affect Big Data adoption and organizational performance.

The dual-theory application is particularly significant, as most previous studies have used either TOE or RBV frameworks in isolation (Lutfi, Al-Khasawneh, et al., 2022). By bridging these frameworks, this study contributes to the body of knowledge for a more comprehensive theoretical lens to explore technology adoption processes. This dual-theory approach builds on prior research that primarily focused on either the TOE or RBV frameworks in isolation (Hashim et al., 2021; M. T. Huynh et al., 2023). By combining these perspectives, the current study closes a major gap in the literature by providing a comprehensive model that captures the complexities of Big Data adoption processes in Malaysia's quickly evolving digital economy.

One of the study's most significant contributions is its empirical investigation of training as a moderating variable, which has been largely underexplored in earlier research. While numerous studies have acknowledged the importance of training, most have only suggested it as a future research direction without empirically assessing its moderating effects (Akter et al., 2016; Q. U. A. Mahmood et al., 2023). This study fills that gap by demonstrating how training enhances or modifies the relationship between key variables and organizational success. For example, it was found that training significantly moderates the relationship between ease of use and performance, emphasizing the importance of user-friendly systems that are complemented by adequate training. This finding aligns with prior research by Alzahrani & Seth (2021), Grover et al. (2018), and Wamba et al. (2017), who highlighted that training reduces employees' cognitive strain and enhances the usability of Big Data technologies.

However, the study also concludes that training has no significant moderating effect on the relationships between data quality management, data security, and top management support with organizational performance. This finding offers crucial theoretical insights into the context-specific effectiveness of training as a moderator. It suggests that while training is vital for improving ease of use, it may be less impactful in other areas, such as data security, which might require distinct organizational approaches.

The absence of significant moderation in these areas does not diminish the value of training but instead highlights its role as a context-specific enabler (Baron & Kenny, 1986). According to Baron & Kenny (1986), a moderator offers context-specific insights, indicating scenarios where the independent variable exerts a greater influence. As Hair Jr. et al. (2017) argued, moderation analysis is designed to identify the specific conditions under which certain relationships exist, and the fact that training significantly moderates ease of use is valuable in itself.

Another contributing factor to the lack of significance for training, particularly in cross-sectional research, could be the use of evaluation methods that do not fully capture its impact, especially when a single-point-in-time approach is used. Training effectiveness often benefits from a longitudinal assessment that tracks changes in knowledge, skills, and competencies before and after the training intervention. A cross-sectional design may not account for the evolution of user capabilities and their influence on performance over time.

According to De Araujo et al. (2019), pre- and post-training assessments are essential for better understanding training efficacy, as training outcomes are best assessed using longitudinal designs that reflect the practical application of newly acquired skills.

Furthermore, Alzahrani & Seth (2021), Grover et al. (2018), and Wamba et al. (2017), argue that training's true impact on technology adoption and performance becomes more apparent after users have had time to apply the training in real-world scenarios, emphasizing the need for a pre-and-post measurement approach to produce more meaningful results.

In the context of Malaysia, where skill shortages and digital literacy gaps have been identified as major barriers to Big Data adoption (Hamzah et al., 2020; Sumathi et al., 2019), the inclusion of training as a moderating factor is particularly significant. This study not only expands the TOE and RBV models but also offers new insights into the dynamics of Big Data adoption that are highly relevant to the practical realities of Malaysia's digital economy.

Another significant theoretical addition of this study is its systematic approach to resolve contradictions in the literature regarding the factors of Big Data adoption and their impact on organizational performance. Previous research has found inconsistent results regarding the importance of several TOE factors (e.g., data quality management, data security, and top management support) in affecting technology adoption outcomes (Al-hiyari et al., 2013; Ghasemaghaei & Calic, 2019). For instance, while Ghasemaghaei (2020) found that data security is crucial, other studies argue that its impact is context-dependent and does not always lead to significant performance gains. Similarly, the relationship between ease of use and organizational performance has been debated, with some studies indicating a positive relationship and others finding a minor effect when fundamental organizational issues are overlooked (Parulian et al., 2023).

By integrating training as a moderating factor, this study offers a reasonable explanation for these inconsistencies, illustrating how the impact of TOE factors depends on workforce preparedness and skill development. This theoretical revision clarifies the conditions under which specific factors have a greater impact, resolving ambiguities in the literature and providing a more consistent framework for understanding Big Data adoption.

Unlike previous studies that have primarily focused on a single determinant or a small set of factors (Ghasemaghaei & Calic, 2019; Parulian et al., 2023), this study develops a comprehensive model that incorporates multiple organizational and environmental determinants specifically data quality management, data security, ease of use, and top management support along with training as a moderator. This integrated approach provides a holistic understanding of how these elements interact to influence Big Data adoption outcomes, leading to a more robust framework than previous research.

This unique integration also addresses the fragmented nature of prior research, which often examines different aspects of Big Data adoption separately, resulting in a piecemeal understanding of the adoption process (Elbanna & Newman, 2022; Smith, 2023). By capturing the interaction of different drivers within a single model, this study offers a fuller and more comprehensive understanding of the complexities of Big Data adoption, enhancing theoretical knowledge in this domain.

In conclusion, this study adds to the literature by presenting a comprehensive, and theoretically grounded framework that enhances understanding of Big Data adoption in Malaysian Digital Status organizations. It expands on the TOE and RBV theories, resolves inconsistencies in the literature, and offers a fresh perspective on the role of training as a moderating factor, making it a unique and valuable contribution to the field of technology adoption studies.

5.4.2 Practical Contributions

This study provides several practical contributions that will benefit key stakeholders, including Malaysia Digital Status companies in the Global Business Services (GBS) sector, practitioners, Malaysia Digital Economy Corporation (MDEC), and Malaysia's national development agenda.

This study provides unique insights into Big Data adoption strategies designed specifically for Malaysia's Digital Status companies in the GBS sector. This study examines the roles of data quality management, data security, ease of use, and top management support to provide practical solutions for addressing the problems associated with Big Data deployment. In particular, no studies in the existing literature have specifically focused on the unique challenges and the combination of factors in the context of GBS companies, who confront the combined difficulty in balancing global operational requirements with local regulatory needs.

The findings highlight the necessity of strong data governance frameworks and data security policies in ensuring the integrity and reliability of Big Data ecosystem. In an industry where operational efficiency and compliance are critical, this study makes concrete recommendations for integrating digital transformation programs with both global operational goals and local regulatory frameworks. GBS companies may reduce risks, improve decision-making, and increase operational efficiency, all of which lead to greater organizational performance.

For business executives and IT managers, this study emphasizes the importance of user-friendly Big Data technologies and top-level management assistance in achieving successful adoption. The study emphasizes the importance of clear strategies that promote ease of use, allowing employees to fully exploit Big Data technologies. This is especially important in the GBS industry, where massive volumes of data are handled daily for operational and customer service purposes.

Furthermore, this study underlines the importance of senior management providing not just strategic direction but also active support for training initiatives aimed at closing the existing skills gap. This is the first study to investigate how top management support and workforce training interact to promote Big Data adoption especially within the context of Global Business Services (GBS). The findings give company executives with information to help them fine-tune their Big Data initiatives, ensuring that their teams have the capabilities needed to fully leverage these technologies. This will make companies quicker and allow decision-makers to use data-driven insights to improve organizational performance. Companies that effectively leverage Big Data and analytics are able to make faster, more informed decisions, optimizing their operations and enhancing competitiveness.

From a policy standpoint, this study provides new empirical insights to government bodies such as MDEC, which are in charge of pushing Malaysia's digital transformation. The findings provide a new understanding of how training functions as a significant moderator in the adoption of Big Data technology by Malaysia Digital Status companies. This is especially relevant because few studies have looked at the moderating function of training in this context, making the findings a vital contribution to policy development.

By identifying training as a critical enabler of Big Data adoption, the study provides policymakers with practical advice on how to create effective upskilling and reskilling programs. These insights may be utilized to create training efforts that fit the changing needs of the digital workforce, ensuring that Malaysia maintains a strong talent pool capable of supporting Big Data adoption across all sectors. Furthermore, the research is consistent with the goals of the Malaysia Digital Economy Blueprint, providing policymakers with tools to enhance existing initiatives and ensure that they are successfully linked with the aspirations of Malaysia Digital Status companies.

By integrating the insights from this study into national training policies, the collaboration between MDEC and HRDF can ensure that Malaysia produces a steady stream of certified data experts. This will ultimately foster a more skilled workforce, ready to support the digital transformation objectives of both individual companies and the nation as a whole.

At the national level, this study contributes to Malaysia's ambitions to become a regional leader in digital transformation and Big Data. By providing fresh insights into the elements that promote effective Big Data adoption, the study aids in aligning company strategy with national goals aimed at promoting economic growth and competitiveness. The findings offer practical recommendations that can help Malaysia

Digital Status companies optimize their data strategy, thereby contributing to major national development goals such as GDP growth, innovation, and global competitiveness.

Moreover, the study’s contributions may be extended beyond Malaysia to ASEAN countries and other regions encountering similar challenges in big data adoption. By offering insights that are adaptable across different cultural and regulatory environments, the study enhances the scalability of its findings, allowing for broader application while addressing Malaysia-specific challenges in Big Data adoption. This adaptability not only strengthens the study’s relevance for Malaysia’s national goals but also provides a framework that can inform digital transformation efforts in diverse contexts, promoting a sustainable model for Big Data integration across ASEAN and globally.

The study provides a complete strategy for enhancing digital infrastructure across Malaysia Digital Status organizations, with a focus on tackling the core concerns of data quality management, data security, and ease of use. Furthermore, the emphasis on training as a moderating element emphasizes the critical role that workforce preparation plays in generating long-term economic growth. This research makes a vital contribution to Malaysia's overall efforts to remain competitive in the global digital economy by ensuring that companies possess a competent workforce capable of properly exploiting Big Data.

5.5 Limitation and Future Research

While this study has made substantial contributions to the understanding of the relationship between key factors impacting Big Data adoption and organizational performance, it is important to acknowledge some limitations. These limitations give critical considerations for future research that builds on the findings provided here.

5.5.1 One-Dimensional Sampling Method

One of the study's primary limitations is the one-dimensional sampling approach used. This study collected data from a single type of respondent within each firm, typically key informants such as managers or data specialists. While this approach was appropriate for gathering insights at the organizational level, it may have provided a biased perspective of the factors impacting Big Data adoption. This one-dimensional approach may limit the depth and variety of perspectives acquired because ideas from other levels of the organizations were not incorporated.

For future studies, a mixed-method approach is highly recommended to address this limitation. By incorporating both quantitative and qualitative data, researchers can capture a more comprehensive understanding of how Big Data adoption influences organizational performance. A multidimensional sample technique that includes people at all levels of the organization such as executives, technical data experts which will enrich the data by reflecting a wider range of opinions. This method may also include in-depth interviews or case studies to investigate the contextual elements that influence how different stakeholders perceive and contribute to Big Data initiatives. Such an approach would produce more nuanced insights and provide a comprehensive picture of organizational dynamics in Big Data adoption.

5.5.2 Single Scope of Sample Group

Another limitation of this study is its exclusive emphasis on companies classified as Malaysia Digital Status (MDS), limiting the findings' generalizability. While this sample group gave useful insights regarding Big Data usage in the digital economy, it did not include other crucial sectors of Malaysia's economic framework, such as agriculture, construction, manufacturing, and services. These industries are critical components of the Malaysia Digital Economy Blueprint, and each may encounter unique difficulties and opportunities as they implement Big Data technologies.

For future studies, expanding the scope to include other sectors is essential for gaining a more complete picture of Big Data adoption across the Malaysian economy. Future studies could look into businesses including agriculture, construction, manufacturing, and services, all of which play important roles in the nation's development. Each of these industries has a unique approach to Big Data, necessitating customized solutions and adoption strategies. Big Data, for example, can help optimize agricultural supply chains and resource management, as well as improve building project planning and efficiency. By widening the sample group, researchers can investigate sector-specific factors impacting Big Data adoption, perhaps leading to more tailored and practical suggestions for organizations across industries. Understanding these industry-specific dynamics will also help policymakers design more focused support systems for industries at different phases of digital transformation.

5.5.3 Cross-Sectional Study Design

Another limitation of this study is the use of a cross-sectional study design, which gathers data at a single point in time. While this approach provides a useful snapshot of relationships between variables, it is not well-suited for capturing the evolving nature of training's impact on Big Data adoption. Training, by its nature, requires time for skills to be absorbed and applied within an organization, making it challenging for a cross-sectional study to adequately measure its full effects. Without the ability to track progress over time, the study may miss key insights into how training influences Big Data utilization and organizational performance after employees have gained experience and adapted their workflows.

Longitudinal research should be used in future studies to address this constraint and provide deeper insights into the shifting effects of big data adoption. A longitudinal technique would enable researchers to track the progress of Big Data deployment over time and measure how its impact on organizational performance changes at each step. This method is especially beneficial for investigating training as a moderating variable because it enables a comparison of organizational outcomes before and after training interventions. Researchers can assess the return on investment (ROI) of training by collecting data at regular intervals and analyzing the long-term effects on the effectiveness of Big Data initiatives. Longitudinal study will also help to clarify temporal connections between variables, providing more evidence for causal interpretations.

Furthermore, a longitudinal approach could investigate how organizational behaviour in the Global Business Services (GBS) sector interacts with outsourcing techniques, particularly in organizations that rely heavily on external suppliers for routine operational activities. This dynamic is especially important in the GBS industry, where organizations frequently outsource crucial operational operations, possibly jeopardizing internal innovation capabilities and long-term strategic goals (Hanafizadeh & Zareravasan, 2020). Future studies that track changes over time may provide valuable insights into how outsourcing strategies influence organizational modelling for Big Data adoption and overall performance, particularly when combined with internal training programs aimed at reducing reliance on external providers.

Future research should also look into how specific factors, such as training, influence performance outcomes in GBS companies that rely significantly on outsourced labor. For example, assessing whether training effectively transfers crucial Big Data skills to internal teams in such situations, or if it falls short due to reliance on third-party expertise, would be extremely important for GBS organizational decision-making (Grover et al., 2018; G. J. Lee, 2020). Longitudinal studies could give evidence on the extent to which training develops a self-sustaining data culture in outsourcing-heavy organizations, as well as its long-term impact on resilience and innovation.

Future study in the GBS sector, where operations frequently span numerous geographical locations with diverse skill requirements, might focus on targeted training solutions that maximize efficiency and increase adaptability in Big Data adoption. A longitudinal assessment would enable GBS companies to observe how strategic training influences organizational readiness, fosters in-house innovation, and improves performance metrics; all of which are critical for organizations seeking to balance cost-effectiveness and innovation potential (Hadidi & Power, 2020). Future research may reveal if well-structured, continual training activities are adequate to retain Big Data capability in-house, or if reliance on external vendors remains a limiting factor to strategic expansion (Akbari, 2024).

Incorporating a longitudinal design overcomes cross-sectional studies' inherent flaws, such as their inability to demonstrate causality or portray the dynamic nature of technological adoption. Future research can provide more accurate forecasts of how Big Data and training contribute to long-term organizational success by measuring their cumulative impact over time. This approach may also record changes in outsourcing strategies and training effectiveness, assisting GBS organizations and governments in refining policies to support long-term growth in Big Data skills and organizational resilience in a competitive digital economy.

A longitudinal design addresses the inherent limitations of cross-sectional research, specifically their inability to capture causality or the evolving nature of technological adoption. Longitudinal study, which tracks the cumulative effects of Big Data and training over time, can provide more detailed insights into their contributions to long-term organizational success. This approach also enables for the study of changes in outsourcing strategies and training efficacy, which provides significant guidance to GBS companies and legislators. Organizations can foster sustainable growth in Big Data competences and increase organizational resilience in a competitive digital economy by fine-tuning policies based on these findings.

5.6 Recommendations

5.6.1 Policy Makers

Policymakers in Malaysia, particularly key agencies such as MDEC and HRDF, play an important role in driving the adoption of Big Data technology across many industries. Recent policy initiatives and strategic programs launched by these authorities demonstrate their continued efforts to assist Malaysia's digital transformation and increase the country's worldwide competitiveness in data management, analytics, and innovation. However, the findings of this study indicate that there is still tremendous potential for policy improvement to address challenges such as data quality, data security, and a shortage of experienced data professionals. This part summarizes the existing policies implemented by MDEC and the government, followed by specific recommendations based on the study findings.

Enhancing Current Policies Introduced by MDEC and the Government

The Malaysian government created the Malaysia Digital Economy Blueprint (MyDIGITAL) in 2021 with the goal of accelerating the country's digital economy and increasing usage of Big Data, AI, and cloud computing. One of the blueprint's key components is talent development in data science and analytics through public-private collaborations. The project emphasizes the importance of digital infrastructure and data-driven decision-making and aims to attract RM70 billion in digital investments by 2025. This effort is critical to establishing Malaysia as a regional leader in Big Data usage (Economic Planning Unit, 2021).

Similarly, MDEC's DataKITA Initiative aims to empower companies through data-driven strategies and promote data governance principles. MDEC's DataKITA program focuses on assisting businesses in using Big Data to improve decision-making and business agility. This campaign also aims to raise cybersecurity awareness to maintain data integrity and security across companies. The effort aims to improve data infrastructure and promote a data analytics culture in companies, preparing them for long-term growth in a data-driven economy (MDEC, 2022b).

Strengthening Data Governance Frameworks

To combat poor data quality, governments should continue to build strong data governance frameworks that ensure data entering organizational systems is structured, reliable, and usable for decision making. For example, the successful implementation of the PADU system demonstrates the significance of high-quality data in policy decisions (BFM, 2024). To replicate this accomplishment across industries, it is critical to establish data ownership legislation and strict data quality standards. This effort is related to the DataKITA initiative, which already promotes best practices in data governance but can be strengthened by incorporating more comprehensive data quality management practices across sectors, particularly in organizations dealing with unstructured data, which currently accounts for up to 80% of all data (Taleb et al., 2018).

Expanding training programs to cover a holistic data ecosystem

While MDEC and HRDF have developed various effective training programs, there is a need for more comprehensive training that addresses the full data ecosystem, from data quality enforcement to data security and top management roles. Training should be adjusted to meet the changing needs of various roles within a company. For example, courses can include modules on establishing data governance, preventing security breaches, and aligning senior management with the organization's data strategy. Employees at all levels will benefit from a thorough grasp of the data lifecycle, which will enable them to properly manage and exploit Big Data technologies. This thorough training program will also improve organizational performance and decision-making processes.

Incentives for Certified Data Experts and Skills Development

To address Malaysia's data professional shortage, it is critical to create incentives for individuals and businesses pursuing certification in Big Data technology. Policymakers could provide tax exemptions, subsidies, or financial incentives to companies that spend in training their employees in data management, data analytics, and cybersecurity. Furthermore, providing incentives to persons pursuing data science certifications can help to close the widening skills gap. MDEC might work with private-sector groups to ensure that these incentives are in line with industry needs, resulting in a consistent stream of certified data experts prepared to meet the demands of the digital economy.

Promoting R&D and Innovation

Policymakers should encourage GBS businesses and other industry participants to engage more extensively in R&D activities aimed at Big Data solutions. Extending the current framework under the MyDIGITAL plan and other programs such as DataKITA to grant R&D tax breaks for innovation in data-driven technologies will not only stimulate local innovation but also position Malaysia as a technological hub. Strengthening collaborations between academia, industry, and government can bolster R&D activities, giving Malaysia a competitive advantage in global data innovation.

Finally, the managerial implications for policymakers involve creating a supportive ecosystem that fosters innovation, strengthens data governance, and enhances talent development, all of which are crucial to ensuring that Big Data technologies and solutions contribute to sustainable economic growth and long-term competitiveness.

The Malaysia Digital Economy Blueprint (MyDIGITAL) and the DataKITA initiative have established a solid platform for digital transformation, but additional improvements, such as those proposed in this study, would handle existing difficulties more effectively. These strategic measures will not only improve organizational performance across sectors, but will also ensure long-term sustainability.

5.6.2 Government/Government Related Agencies/ Investors

To establish Malaysia as a global leader in the digital economy, the Government of Malaysia has launched two key initiatives: the Malaysia Digital Economy Blueprint (MyDIGITAL) and the National Fourth Industrial Revolution (4IR) Policy. These initiatives are designed to accelerate the country's digital transformation, enhance economic competitiveness, and position Malaysia as a digital hub in the region and beyond. The findings of this study provide key recommendations that directly support the objectives of these initiatives, focusing on areas such as data governance, research and development (R&D), and workforce upskilling to drive innovation and growth in the digital economy.

The study suggests that the government approach data as a national asset, in line with MyDIGITAL's aims, which emphasize the importance of data management in supporting the digital economy. By creating a robust data governance structure, the government can ensure that data is valued as a national resource. This approach should prioritize data quality, ownership, and security to improve decision-making reliability and accelerate economic growth. By supporting this recommendation would enable the MyDIGITAL program to fully capitalize on Big Data to increase public sector efficiency and build a data-driven economy. MyDIGITAL aims to boost the digital economy's contribution to Malaysia's GDP to 22.6% by 2025, which can be accomplished by addressing critical data governance issues (Economic Planning Unit, 2021).

To support the National 4IR Policy, this study suggests that the government prioritize R&D and innovation in Big Data technology. Agencies such as MDEC and HRDF should implement policies that stimulate research and development in order to create breakthrough Big Data solutions. These policies will ensure that Malaysia Digital Status companies have the necessary instruments to improve operational efficiency and organizational performance. The National 4IR Policy stresses the use of emerging technologies like Big Data, AI, and automation to alter industries, boost productivity, and open up new growth prospects (PwC, 2021). Promoting innovation in Big Data technologies will be consistent with the policy's goal of promoting these technologies and establishing Malaysia as a hub for digital innovation.

Finally, these ideas clearly support MyDIGITAL's strategic objectives and the National 4IR Policy. By prioritizing data governance and encouraging R&D and innovation, Malaysia can expedite its digital transformation and realize its aim of becoming a regional leader in the Fourth Industrial Revolution.

5.6.3 Global Business Services Companies

Malaysia Global Business Services (GBS) businesses are uniquely positioned to accelerate Big Data adoption due to their existing infrastructure and skills. These companies, which are critical to the Malaysia Digital Economy Corporation's (MDEC) agenda, can use their facilities to facilitate wider use of Big Data technology. By improving their internal processes and partnering with government agencies, GBS organizations may drive innovation, foster a data-driven culture, and assure long-term viability.

GBS companies can boost Big Data adoption by leveraging their current facilities, such as shared service centers and digital hubs. These facilities already have modern technology and competent workers, making them a perfect foundation for integrating Big Data solutions into day-to-day company operations. To realize this potential, GBS companies should prioritize improving their digital infrastructure and investing in advanced analytics tools. This will allow for the smooth processing and management of huge datasets, increasing decision-making skills and operational efficiency.

Collaboration across GBS businesses, MDEC, and HRDF is crucial in enabling this transition in response to the increased demand for Big Data skills. This collaboration can help establish specialized training programs that focus on upskilling the workforce in Big Data technology. GBS companies should collaborate closely with MDEC and HRDF to develop certification pathways that incentivize employees to obtain Big Data certifications, ensuring that they have the skills required to manage and analyze data successfully. These coordinated initiatives will not only alleviate Malaysia's data specialist shortfall, but will also improve the country's entire talent pool, boosting its worldwide competitiveness.

To encourage the certification of additional Big Data professionals, the government and GBS companies may consider offering financial incentives, subsidies, or tax breaks to individuals and organizations who invest in these credentials. By incentivizing the use of Big Data training, GBS companies can ensure a continual growth in competent people who can use data to improve business performance. This will also help to retain talent in the country, minimizing dependency on foreign expertise and encouraging domestic innovation.

In addition to people development, GBS businesses must spend in R&D and innovation. R&D investments centered on Big Data technology will not only assist GBS companies improve their service offerings, but will also allow them to remain competitive in a fast-evolving industry. GBS companies can collaborate with research organizations and universities to develop creative solutions that improve their ability to analyze data, foresee trends, and improve business outcomes. Such investments will set off a virtuous cycle of innovation, allowing GBS companies to continuously improve their Big Data skills while driving economic growth.

Furthermore, fostering a data-driven culture inside GBS companies is critical to reaping the full benefits of Big Data adoption. GBS companies should promote continual learning and create a climate in which data is key to decision-making processes. GBS companies may increase productivity, cut costs, and uncover new market opportunities by incorporating data analytics into their everyday operations and strategic planning. A robust data-driven culture will not only increase organizational performance, but will also position GBS companies as regional digital transformation leaders.

GBS companies should prioritize sustainability and long-term vision on Big Data adoption plans. This necessitates a forward-thinking strategy that balances present operational objectives with future requirements. GBS companies must invest in environmentally friendly technology such as energy-efficient data centers, as well as plan for long-term scalability of their Big Data platforms. By taking a long-term perspective, GBS companies can ensure that their Big Data investments not only drive immediate commercial success but also contribute to the SDGs, particularly in areas such as economic growth and innovation. Figure 5.1 illustrates the significance of resolving the problems associated with Big Data adoption, which are indicated by the low acceptance rate of Big Data solutions and a talent scarcity of data specialists. Both of these concerns are clearly highlighted as fundamental challenges that necessitate policy interventions.

5.6.4 Sustainable Development Growth (SDG) Agenda

In a global aspect, Big Data is critical for discovering new insights, and its significance has been integrated into the agenda of the United Nations' Sustainable Development Goals (SDGs) launched in 2015. The United Nations' recognition of Big Data's benefits emphasizes its importance in improving the understanding and implementation of sustainable development programs. According to a United Nations report (Nation, 2015), Big Data is widely discussed for its applications in pattern recognition, predictive modelling, data monitoring, and neural networks, all of which are useful in detecting causal links and accomplishing the SDGs.

For example, capability of analytics in Big Data is essential for offering insights into trends, patterns, and correlations that are pertinent to sustainable development. By leveraging these advanced analytics techniques, policymakers in countries participating in the SDGs agenda can better identify opportunities and challenges across various domains, such as economic growth, environmental conservation, and social equity.

For instance, predictive modelling and pattern recognition can help forecast environmental changes and their impacts on different ecosystems, enabling proactive measures for environmental conservation. Similarly, data monitoring can track progress in social equity initiatives, highlighting areas where interventions are needed to address any demographic gaps. Neural networks and other advanced computational methods can uncover complex interactions and causal relationships within the data, providing a deeper understanding of how different factors influence sustainable development outcomes.

In Malaysia, Malaysia Digital Status companies play an important role in furthering the country's contribution to the SDGs. These companies are at the forefront of driving digital transformation, using Big Data Analytics to generate long-term solutions that connect with the SDGs. For example, they use Big Data to boost economic growth by spotting market trends and improving resource allocation, therefore contributing to the SDG target of decent work and economic growth.

Furthermore, Malaysia Digital Status companies play an important role in environmental conservation by using Big Data Analytics for monitoring alerts or predictive analytics. This contributes to the SDG target of life on land and life below water by encouraging sustainable activities and reducing environmental consequences. The integration of Big Data Analytics into the SDGs framework represents a significant advancement in the ability to monitor and evaluate the progress of sustainable development initiatives. In 2015, the United Nations Sustainable Development Goals ; BIG SDGs (2016) introduced a comprehensive blueprint for action which comprises 17 SDGs objectives and 169 metrices to end poverty, save the environment, and guarantee everyone's prosperity. The urgency of sustainable development arises from interconnected environmental, social, and economic challenges facing humanity today, including climate change, biodiversity loss, poverty, inequality, and social injustice. These complex issues require a holistic and integrated approach to development, emphasizing equity, resilience, and long-term viability (Nation, 2015; Rockström et al., 2009). Achieving these ambitious goals by 2030 demands collaborative efforts from governments, businesses, civil society, and academia, highlighting the need for interdisciplinary collaboration and innovative solutions (Nation, 2015).

In summary, the utilization of Big Data in the context of sustainable development has opened new avenues for understanding and addressing global challenges. By harnessing the power of advanced analytics, countries can make informed decisions that drive economic growth, protect the environment, and promote social equity, ultimately contributing to the achievement of the Sustainable Development Goals.

To conclude the connectivity of the discussion between chapters, figure 5.1 provides the visual view of problem tree analysis that highlights the cause-and-effect relationship, and how training plays its role to solve the issues with the illustration of the contribution factors.

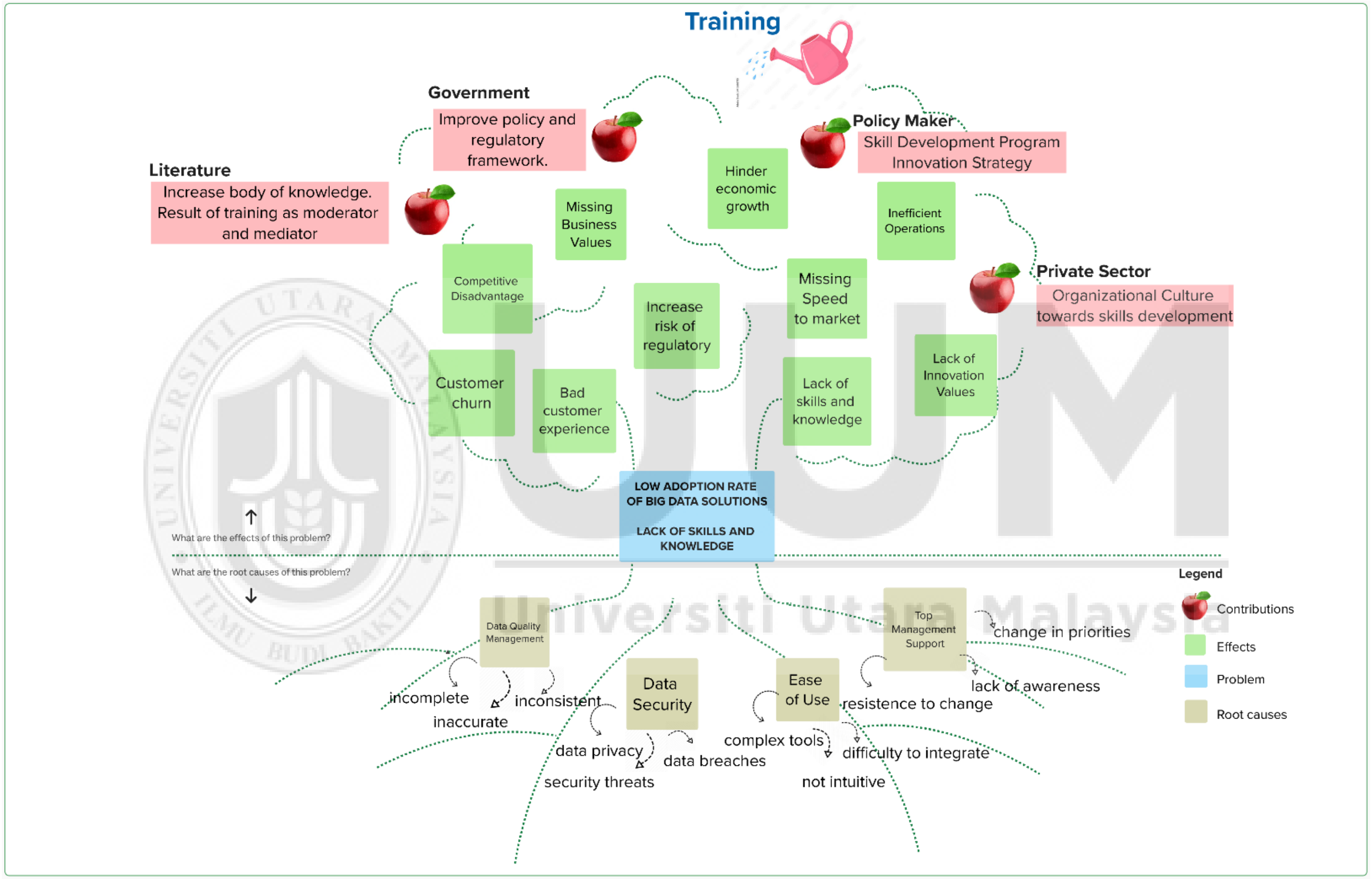

Figure 5.1
Problem Tree Analysis

5.7 Overall Framework of the Thesis Integration with Contributions

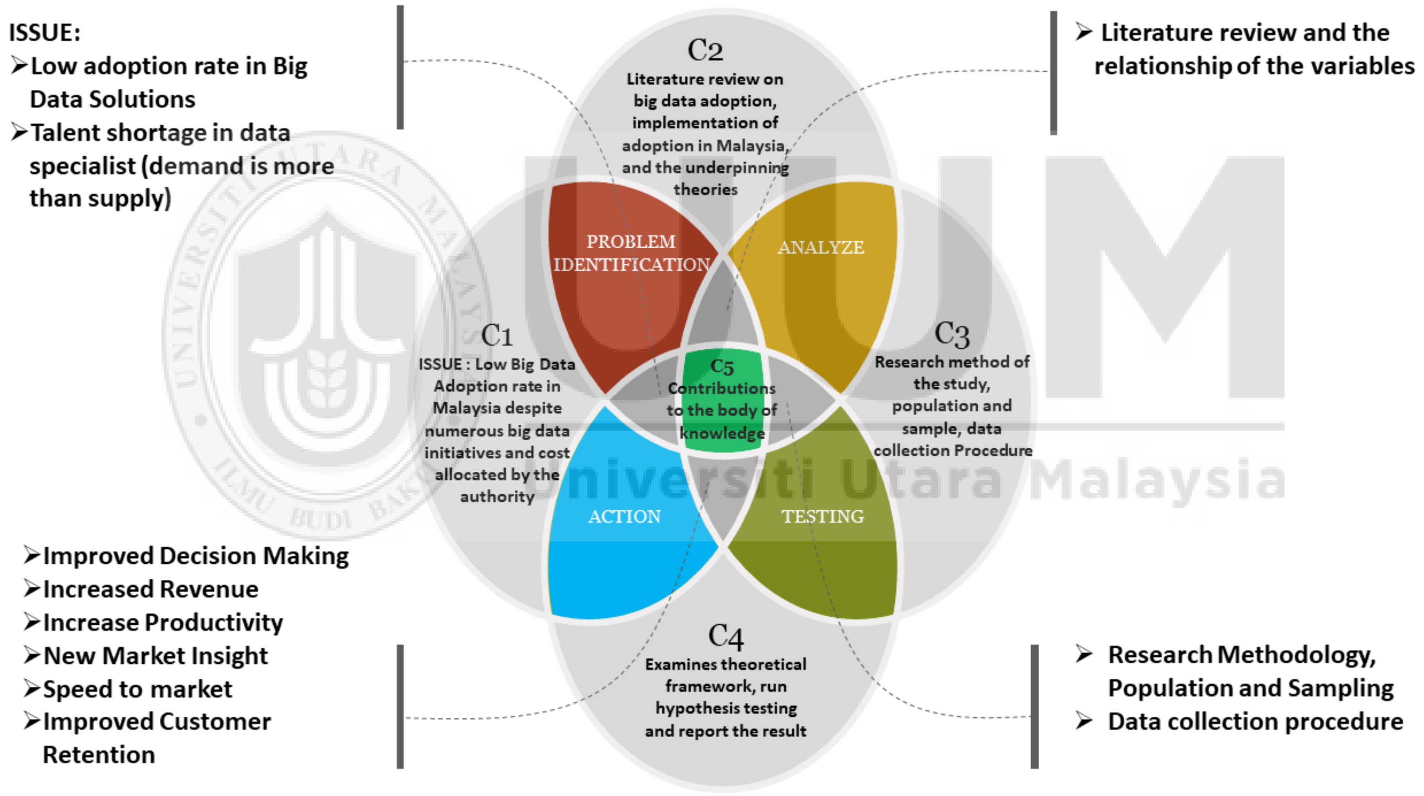

Figure 5.2
Thesis Connection Ring

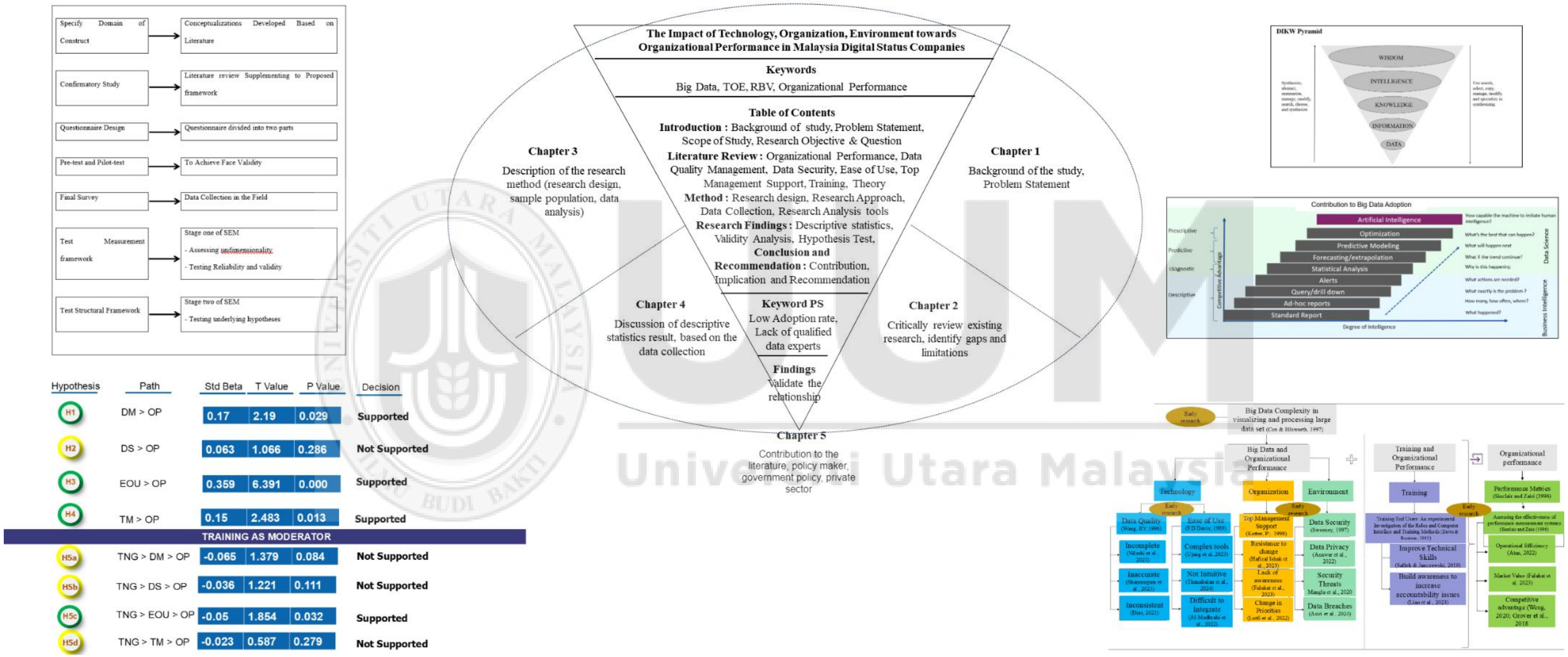

Figure 5.3
Full Research Framework and Methodology Employed in the Study

5.8 Conclusion

This study examined the impact of Technology, Organization, and Environment on Organizational Performance for Big Data Adoption in Malaysian Digital Status Companies, focusing on the critical challenges and opportunities encountered by Global Business Services (GBS) organizations in Malaysia amidst rapid digital transformation driven by Industry 4.0. Given that merely 36% of companies have embraced innovative technologies as reported by National Business Digital Adoption Index (2022) and a projected shortage of up to 15,000 skilled data professionals (Yusoff et al., 2021), the study highlights the necessity for systematic approaches to improve Big Data adoption. Despite governmental and private sector efforts, including the Malaysia Digital Economy Blueprint, adoption rates persist at low levels, hindered by inadequate data analytics capabilities, strategy misalignment, and a considerable skills deficit that impacts successful data usage (Oi, 2022; Randstad, 2022). This study addresses existing gaps by offering a thorough investigation of Big Data adoption in Malaysia, integrating Technology-Organization-Environment (TOE) framework and Resource-Based View (RBV) theory.

Using the Technology-Organization-Environment (TOE) framework and Resource-Based View (RBV) theory, the study identified significant elements that influence organizational performance in this environment. The study specifically addressed challenges such as low adoption of Big Data solutions and a shortage of skilled data professionals, as shown in Figure 5.1 (Problem Tree Analysis). The results, depicted in Figures 5.2 (Thesis Connection Ring) and 5.3 (Full Research Framework and Methodology), validate the suggested correlations between major Big Data adoption determinants and organizational performance. The complete methodology presented in this study offers a structured approach to understanding the impact of these factors on the GBS sector. By using training as a moderator, the study investigated how these factors can improve the relationship with organizational performance.

Figure 5.2 (Thesis Connection Ring) depicts the iterative process of problem identification, analysis, testing, and implementation. It begins with the recognition of critical issues, such as the low adoption rate of Big Data solutions and talent shortage in Malaysia, that establish the focus of the literature review and methodology in subsequent chapters.

Similarly, Figure 5.3 (Full Research Framework and Methodology) provides an overview of the research design and organization. It explains how each chapter helps to achieve the larger aim of understanding and overcoming Big Data adoption difficulties. Beginning with the problem identification in Chapter 1, the figure illustrates the theoretical frameworks, hypotheses, and procedures used, eventually culminating to the analysis and conclusions in Chapter 4 and recommendations in Chapter 5. This systematic method ensures that the study stays on track while addressing real-world difficulties encountered by GBS companies.

Using a quantitative approach, data were collected from 272 respondents within GBS companies and analyzed using Partial Least Squares Structural Equation modeling (PLS-SEM) through SmartPLS 4.1.0.0. The analysis examined eight hypotheses, four of which were supported. The findings revealed that data quality management, ease of use, and top management support had a significant positive influence on organizational performance, however data security had no significant effect. The moderating impact of training was discovered to be critical, as it considerably improved the relationship between ease of use and organizational performance, underlining the need of user-friendly technologies combined with appropriate training.

This evidence outlines the foundation for practical, actionable recommendations targeted at policymakers, governmental entities, and companies to enhance Big Data strategy and training programs. These recommendations are consistent with Malaysia's national digital transformation agenda, including the Malaysia Digital Economy Blueprint, and facilitate the nation's overarching objectives of economic growth and innovation.

The findings demonstrated that data quality management, ease of use, and top management support significantly influence organizational performance in the context of Big Data adoption, while data security did not show a substantial impact. Furthermore, training was found to play a critical moderating role, particularly in enhancing the influence of ease of use on performance outcomes. These results shed light on how companies may strategically improve performance through targeted training and better management of Big Data adoption factors.

From a practical standpoint, the findings offer actionable recommendations for policymakers, government agencies, and businesses to improve Big Data strategies and training programs. Equally important is the ethical dimension, which ensures the transparency and truthfulness of insights derived from data.

Beyond practical implications, this study intends to shed lights on the importance of ethical dimension to Big Data adoption by emphasizing the importance of data integrity. The Quran advises, “And do not mix the truth with falsehood or conceal the truth while you know [it]” (Quran 2:42). This verse emphasizes the ethical obligation to uphold truthfulness and transparency in data handling, especially within Big Data, where the quality and accuracy of information significantly influence strategic decision-making. Ensuring data integrity is not only a technical necessity but also a moral duty, as it safeguards against risks associated with misinformation, builds trust among stakeholders, and reinforces a culture of accountability.

From a theoretical standpoint, this study expands the existing frameworks by integrating training as a moderating factor within the Technology-Organization-Environment (TOE) and Resource-Based View (RBV) frameworks, providing a deeper understanding of how organizational and environmental elements interact to influence Big Data adoption outcomes.

The conclusion of this study provides a roadmap for companies aiming to adopt Big Data solutions to enhance performance and competitiveness. Practical recommendations derived from the findings can guide policymakers, government agencies, and business leaders in refining Big Data strategies and developing targeted training programs, aligning with Malaysia's national digital transformation initiatives such as the Malaysia Digital Economy Blueprint. This research also presents multiple avenues for future study and may be replicated in other sectors to broaden understanding of Big Data adoption across industries.

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APPENDICES

APPENDIX 1

SAMPLE OF QUESTIONNAIRE

SURVEY ON DETERMINANTS BIG DATA ADOPTION WITH MODERATING EFFECT OF TRAINING FOR MALAYSIA DIGITAL STATUS COMPANIES

Information:

This survey is to determine the impact of Big Data Analytics Adoption on organizational performance in leading data-driven decisions. This survey is to confirm the understanding of your planned intent to use Big Data Analytics in your business processes and activities. The researcher believes that the outcome of this research will be of immense benefit to improve decision performance in Malaysian companies. Your effort in filling in the questionnaires is highly appreciated in order to produce accurate and quality research.

Introduction:

Big Data is a terminology to illustrate the massive volume of data that due to large size and complexity, managing the data has gone beyond the traditional tools. Big Data Analytics (BDA) is the application of analytic techniques to uncover information.

Section 1: Demographic Information

This section is for background information of the participants to give context to survey data and better analyze the result of following sections.

Gender *

- Male
- Female

Age *

1. Below 29
2. 30 - 39
3. 40 - 49
4. 50 - 59

Education Level *

1. Certificate
2. Diploma
3. Bachelor
4. Master
5. Doctorate

Level of Position *

1. Senior Management/C-level
2. Middle Management
3. Professionals
4. Supporting Staff

Industry *

1. Consulting/Profession Services
2. Education
3. Financial Services
4. Food and Beverages
5. Government
6. Healthcare
7. Manufacturing
8. Oil and Gas
9. Retatil/wholesale/distribution
10. Telecommunications
11. Technology
12. Transportation/logistics

Number of Employees *

1. ≤ 200
2. 201- 400
3. 401- 800
4. 801- 1000
5. ≥ 1001

Years of Experience *

1. Less than 5 years
2. 5 to 10 years
3. 11 to 20 years
4. More than 20 years

Section 2: Impact of TOE towards Organizational Performances

Section 3 of 8

Section 1 out of 6: Data Management Quality

- Lack of proper data management can affect organizations with incompatible data silos, inconsistent data point and data quality. This section aims to evaluate how data quality can determine the adoption rate for organizations when it comes to big data adoption.

1. The organization recognized the complexity of data quality due its large volume, velocity, and variety. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

2. The organization has a clearly defined strategy for Data Quality Management. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

3. There is a clear ownership of data within the organization. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

4. There is a complete reference model for Data Quality and its Management in Big Data. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

5. There is a centralized data warehouse to consolidate data from various sources. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

6. The organization uses right assessment scheme and quality measurement to address Big Data Quality issues. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

7. The organization established Data Governance to achieve common goals to address data quality across functions. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

Section 4 of 8

Section 2 out of 6: Data Security Protection

- The rapid expansion of data creates concerns about database security to ensure the integrity and privacy of sensitive information.

This section aims to evaluate the security risks associated with the demands of adopting data analytics to generate valuable insights.

1. The organization is aware of the risk of legal repercussions and reputational damage if a security breach of corporate big data occurs. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

2. The complexity in various regulatory and compliance processes hinders the exploration of data insights. *

3. The organization implemented security awareness programs to foster a data security protection culture. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

4. The organization established security policies and controls guidelines to manage data protection culture. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

5. The organization possess a strong authentication mechanism to manage access control to the corporate database. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

6. The organization is willing to invest in a highly secured data detection tool to prevent the breach of corporate data. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

7. The organization embarked on the ethical code of conduct as ethical checks when conducting Big Data projects. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

Section 5 of 8

Section 3 out of 6: Top Management Support

- To bring a meaningful impact on Big Data, having a culture of change within the organization is a necessity.

This section aims to examine top management support in the execution of Big Data Adoption within organizations.

1. The leadership team demonstrated good knowledge of Big Data projects. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

2. A managerial (c-level) role (eg: Chief Data Officer) is created to manage the response of Big Data Adoption. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

3. The leadership team is united across the divisions to support Big Data projects. *

1	2	3	4	5

4. The Big Data Analytics Project is included in the organization's transformation play. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

5. The leadership team is clear about what type of training needs to be provided to increase the skills in Big Data. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

6. The leadership team has a good career development plan for high-skilled employees to pursue Big Data projects. *

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

7. The leadership team connects high-skilled employees with business leader to make a difference with Big Data Projects. *

1	2	3	4	5

Section 6 of 8

Section 4 out of 6: Perceived Ease of Use

- The perceived ease of use was described as how well a user can a can handle the system and the ease of getting the system to do what is required.

This section aims to evaluate the ease of use level of big data analytics techniques/tools in increasing the adoption of big data in organizations.

1. Big Data Analytics is simple to apply.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

2. Big Data Analytics would require fewer steps to discover insights.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

3. Big Data Analytics would enable me to accomplish tasks quickly.

	1	2	3	4	5	
Lowest Agreement	◯	◯	◯	◯	◯	Highest Agreement

4. Big Data Analytics would require advance skills to analyze.

	1	2	3	4	5	
Lowest Agreement	◯	◯	◯	◯	◯	Highest Agreement

5. Big Data Analytics would improve my job performance.

	1	2	3	4	5	
Lowest Agreement	◯	◯	◯	◯	◯	Highest Agreement

6. Big Data Analytics would enhance the capability to complete work effectively.

	1	2	3	4	5	
Lowest Agreement	◯	◯	◯	◯	◯	Highest Agreement

7. I find Big Data Analytics useful for my job.

	1	2	3	4	5	
Lowest Agreement	◯	◯	◯	◯	◯	Highest Agreement

Section 7 of 8

Section 5 of 6: Organizational Performance

- Organizational performance refers to the capability related to the accomplishments of its goals and stakeholders' expectations along with market survival.

This section is to examine the adoption of Big Data Analytics in achieving data-driven decision making that leads to increased performance of the organization.

1. The organization performance has improved its operational landscape and shown interest in Big Data Analytics.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

2. The organization was able to introduce new innovations with the adoption of Big Data Analytics.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

3. Big Data Analytics capabilities accelerate and improve the decision-making process.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

4. Big Data Analytics adoption increased ROI (Return on Investment) for the organization.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

5. Big Data Analytics adoption accelerated the cost reduction / cost avoidance for the organization.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

6. Big Data Analytics adoption improved customer experience and retention through analytical capabilities.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

7. With accurate predictions through Big Data Analytics, the organization has gained the competitive advantage.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

Section 8 of 8

Section 6 of 6: Training

- Organizations need to provide training programs to encourage employees' to use innovation more effectively.

This section is to evaluate the impact of training contributing to the overall goals of the organization's performance in implementing Big Data Analytics adoption.

1. There is an interest from all levels to understand the value of Big Data Analytics.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

2. The organization is willing to invest in trainings to upskill the resources.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

3. There are enough materials for self-learning.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

4. Training would increase my skills in Big Data Analytics.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

5. Training would increase the usability of Big Data Analytics.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

6. I am able to put into practice what I've learned about Big Data Analytics.

Linear scale

1 to 5

1 Lowest Agreement

5 Highest Agreement

Required

7. There are sufficient high-skilled resources to train big data.

	1	2	3	4	5	
Lowest Agreement	○	○	○	○	○	Highest Agreement

APPENDIX 2

RESULT FOR MISSING VALUES

Case Processing Summary						
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
DM1	1	100.00%	0	0.00%	1	100.00%
DM2	2	100.00%	0	0.00%	2	100.00%
DM3	3	100.00%	0	0.00%	3	100.00%
DM4	4	100.00%	0	0.00%	4	100.00%
DM5	5	100.00%	0	0.00%	5	100.00%
DM6	6	100.00%	0	0.00%	6	100.00%
DM7	7	100.00%	0	0.00%	7	100.00%
DS1	8	100.00%	0	0.00%	8	100.00%
DS2	9	100.00%	0	0.00%	9	100.00%
DS3	10	100.00%	0	0.00%	10	100.00%
DS4	11	100.00%	0	0.00%	11	100.00%
DS5	12	100.00%	0	0.00%	12	100.00%
DS6	13	100.00%	0	0.00%	13	100.00%
DS7	14	100.00%	0	0.00%	14	100.00%
TM1	15	100.00%	0	0.00%	15	100.00%
TM2	16	100.00%	0	0.00%	16	100.00%
TM3	17	100.00%	0	0.00%	17	100.00%
TM4	18	100.00%	0	0.00%	18	100.00%
TM5	19	100.00%	0	0.00%	19	100.00%
TM6	20	100.00%	0	0.00%	20	100.00%
TM7	21	100.00%	0	0.00%	21	100.00%
EOU1	22	100.00%	0	0.00%	22	100.00%
EOU2	23	100.00%	0	0.00%	23	100.00%
EOU3	24	100.00%	0	0.00%	24	100.00%
EOU4	25	100.00%	0	0.00%	25	100.00%
EOU5	26	100.00%	0	0.00%	26	100.00%
EOU6	27	100.00%	0	0.00%	27	100.00%
EOU7	28	100.00%	0	0.00%	28	100.00%
OP1	29	100.00%	0	0.00%	29	100.00%
OP2	30	100.00%	0	0.00%	30	100.00%
OP3	31	100.00%	0	0.00%	31	100.00%
OP4	32	100.00%	0	0.00%	32	100.00%
OP5	33	100.00%	0	0.00%	33	100.00%
OP6	34	100.00%	0	0.00%	34	100.00%
OP7	35	100.00%	0	0.00%	35	100.00%
TNG1	36	100.00%	0	0.00%	36	100.00%
TNG2	37	100.00%	0	0.00%	37	100.00%
TNG3	38	100.00%	0	0.00%	38	100.00%
TNG4	39	100.00%	0	0.00%	39	100.00%
TNG5	40	100.00%	0	0.00%	40	100.00%
TNG6	41	100.00%	0	0.00%	41	100.00%
TNG7	42	100.00%	0	0.00%	42	100.00%

APPENDIX 3

DESCRIPTIVE STATISTIC OF THE CONSTRUCT

Variables	Count of Item	Items	N	Minimum	Maximum	Mean	Standard deviation
Data quality management (DM)	1	DM1	272	1.00	5.00	4.136	0.836
	2	DM2	272	1.00	5.00	3.746	0.965
	3	DM3	272	1.00	5.00	3.776	0.961
	4	DM4	272	1.00	5.00	3.625	0.951
	5	DM5	272	1.00	5.00	3.761	1.039
	6	DM6	272	1.00	5.00	3.596	0.988
	7	DM7	272	1.00	5.00	3.934	0.96
Data Security (DS)	8	DS1	272	1.00	5.00	4.081	0.871
	9	DS2	272	1.00	5.00	3.882	0.871
	10	DS3	272	1.00	5.00	3.923	0.961
	11	DS4	272	1.00	5.00	4.029	0.947
	12	DS5	272	1.00	5.00	3.923	0.995
	13	DS6	272	1.00	5.00	3.827	0.949
	14	DS7	272	1.00	5.00	3.926	0.96
Ease of Use (EOU)	15	EOU2	272	1.00	5.00	3.64	0.933
	16	EOU3	272	1.00	5.00	4.059	0.76
	17	EOU4	272	1.00	5.00	3.996	0.86
	18	EOU5	272	1.00	5.00	4.154	0.771
	19	EOU6	272	1.00	5.00	4.066	0.833
	20	EOU7	272	1.00	5.00	3.985	0.923
Organizational Performance (OP)	21	OP1	272	1.00	5.00	3.871	0.88
	22	OP2	272	1.00	5.00	3.739	0.88
	23	OP3	272	1.00	5.00	4.007	0.809
	24	OP4	272	1.00	5.00	3.915	0.811
	25	OP5	272	1.00	5.00	3.956	0.835
	26	OP6	272	1.00	5.00	4.004	0.769
	27	OP7	272	1.00	5.00	4.011	0.76
Top Management Support (TM)	28	TM1	272	1.00	5.00	3.824	0.965
	29	TM2	272	1.00	5.00	3.566	1.066
	30	TM3	272	1.00	5.00	3.75	1.009
	31	TM4	272	1.00	5.00	3.746	0.973
	32	TM5	272	1.00	5.00	3.713	0.999
	33	TM6	272	1.00	5.00	3.621	1.064
	34	TM7	272	1.00	5.00	3.665	1.001
Training (TNG)	35	TNG1	272	1.00	5.00	3.71	0.939
	36	TNG2	272	1.00	5.00	3.688	0.967
	37	TNG4	272	1.00	5.00	4.224	0.711
	38	TNG5	272	1.00	5.00	4.092	0.769
	39	TNG6	272	1.00	5.00	3.926	0.815

APPENDIX 4

RESULTS OF SKEWNESS AND KURTOSIS

Factor	Items	Mean	Standard Deviation	Skewness	Excess Kurtosis
Data quality management (DM)	DM1	4.136	0.836	-0.717	0.064
	DM2	3.746	0.965	-0.409	-0.451
	DM3	3.776	0.961	-0.436	-0.514
	DM4	3.625	0.951	-0.375	-0.334
	DM5	3.761	1.039	-0.656	-0.121
	DM6	3.596	0.988	-0.475	-0.118
	DM7	3.934	0.96	-0.669	-0.237
Data Security (DS)	DS1	4.081	0.871	-0.729	0.185
	DS2	3.882	0.871	-0.407	-0.359
	DS3	3.923	0.961	-0.743	0.215
	DS4	4.029	0.947	-0.817	0.048
	DS5	3.923	0.995	-0.699	-0.239
	DS6	3.827	0.949	-0.557	-0.206
	DS7	3.926	0.96	-0.655	-0.147
Ease of Use (EOU)	EOU2	3.64	0.933	-0.453	0.051
	EOU3	4.059	0.76	-0.605	0.512
	EOU4	3.996	0.86	-0.656	0.226
	EOU5	4.154	0.771	-0.758	0.649
	EOU6	4.066	0.833	-0.662	0.11
	EOU7	3.985	0.923	-0.647	-0.028
Top Management Support (TM)	TM1	3.824	0.965	-0.462	0.007
	TM2	3.566	1.066	-0.409	-0.012
	TM3	3.75	1.009	-0.642	0.541
	TM4	3.746	0.973	-0.508	0.531
	TM5	3.713	0.999	-0.603	0.324
	TM6	3.621	1.064	-0.493	0.236
	TM7	3.665	1.001	-0.373	-0.303
Organizational Performance (OP)	OP1	3.871	0.88	-0.453	-0.531
	OP2	3.739	0.88	-0.421	-0.516
	OP3	4.007	0.809	-0.41	-0.639
	OP4	3.915	0.811	-0.46	-0.434
	OP5	3.956	0.835	-0.489	-0.349
	OP6	4.004	0.769	-0.394	-0.469
	OP7	4.011	0.76	-0.417	-0.434
Training (TNG)	TNG1	3.71	0.939	-0.54	0.019
	TNG2	3.688	0.967	-0.491	-0.093
	TNG4	4.224	0.711	-0.664	0.297
	TNG5	4.092	0.769	-0.599	0.334
	TNG6	3.926	0.815	-0.438	-0.064

APPENDIX 5

FACTOR ANALYSIS AND LOADINGS OF THE ITEMS

	Data quality management	Data Security	Ease of Use	Organizational Performance	Top Management Support	Training
DM1	**0.637**	0.338	0.44	0.457	0.486	0.386
DM2	**0.849**	0.436	0.355	0.519	0.647	0.447
DM3	**0.795**	0.434	0.325	0.499	0.543	0.405
DM4	**0.824**	0.395	0.308	0.502	0.698	0.435
DM5	**0.807**	0.518	0.285	0.478	0.577	0.381
DM6	**0.851**	0.547	0.346	0.498	0.718	0.433
DM7	**0.731**	0.534	0.315	0.487	0.546	0.373
DS1	0.398	**0.709**	0.424	0.43	0.316	0.384
DS2	0.412	**0.689**	0.339	0.408	0.369	0.361
DS3	0.486	**0.852**	0.395	0.445	0.442	0.348
DS4	0.493	**0.86**	0.405	0.453	0.421	0.351
DS5	0.508	**0.879**	0.394	0.434	0.45	0.387
DS6	0.479	**0.778**	0.378	0.423	0.462	0.348
DS7	0.487	**0.836**	0.363	0.44	0.425	0.357
EOU2	0.301	0.42	**0.569**	0.482	0.329	0.441
EOU3	0.292	0.408	**0.772**	0.534	0.279	0.493
EOU4	0.299	0.383	**0.688**	0.482	0.366	0.445
EOU5	0.331	0.385	**0.844**	0.576	0.291	0.567
EOU6	0.367	0.305	**0.831**	0.592	0.353	0.518
EOU7	0.314	0.249	**0.702**	0.526	0.329	0.536
OP1	0.591	0.514	0.556	**0.799**	0.583	0.615
OP2	0.579	0.572	0.501	**0.785**	0.58	0.576
OP3	0.518	0.424	0.631	**0.831**	0.512	0.626
OP4	0.452	0.439	0.623	**0.847**	0.502	0.59
OP5	0.416	0.349	0.628	**0.829**	0.428	0.561
OP6	0.513	0.36	0.555	**0.777**	0.483	0.572
OP7	0.464	0.395	0.596	**0.794**	0.458	0.59
TM1	0.636	0.386	0.399	0.534	**0.832**	0.477
TM2	0.651	0.454	0.33	0.508	**0.796**	0.423
TM3	0.707	0.461	0.427	0.563	**0.884**	0.556
TM4	0.688	0.474	0.382	0.532	**0.880**	0.481
TM5	0.627	0.404	0.354	0.52	**0.872**	0.451
TM6	0.597	0.406	0.298	0.525	**0.832**	0.438
TM7	0.683	0.491	0.417	0.569	**0.886**	0.468
TNG1	0.468	0.324	0.434	0.578	0.561	**0.737**
TNG2	0.41	0.44	0.434	0.522	0.485	**0.702**
TNG4	0.312	0.344	0.626	0.561	0.285	**0.807**
TNG5	0.424	0.229	0.563	0.539	0.394	**0.784**
TNG6	0.348	0.37	0.502	0.551	0.354	**0.741**

APPENDIX 6

SIGNIFICANCE OF THE FACTOR LOADINGS

Coding	Construct	Loading	Sample Mean
DM1	Data quality management	0.637	4.136
DM2		0.849	3.746
DM3		0.795	3.776
DM4		0.824	3.625
DM5		0.807	3.761
DM6		0.851	3.596
DM7		0.731	3.934
DS1	Data Security	0.709	4.081
DS2		0.689	3.882
DS3		0.852	3.923
DS4		0.86	4.029
DS5		0.879	3.923
DS6		0.778	3.827
DS7		0.836	3.926
EOU2	Ease of Use	0.569	3.64
EOU3		0.772	4.059
EOU4		0.688	3.996
EOU5		0.844	4.154
EOU6		0.831	4.066
EOU7		0.702	3.985
OP1	Organizational Performance	0.799	3.824
OP2		0.785	3.566
OP3		0.831	3.75
OP4		0.847	3.746
OP5		0.829	3.713
OP6		0.777	3.621
OP7		0.794	3.665
TM1	Top Management Support	0.832	3.871
TM2		0.796	3.739
TM3		0.884	4.007
TM4		0.88	3.915
TM5		0.872	3.956
TM6		0.832	4.004
TM7		0.886	4.011
TNG1	Training	0.737	3.71
TNG2		0.702	3.688
TNG4		0.807	4.224
TNG5		0.784	4.092
TNG6		0.741	3.926

APPENDIX 7

APPENDIX 7

RESEARCH ARTICLE #1

Title of Article: A conceptual Framework for Big Data Analytics Adoption towards Organizational Performance in Malaysia

Publisher: Uitm.edu.my

Year published: 2022

Volume: Volume 12

Page: 54-62

Issue: 1

Name of Journal: Journal of Information and Knowledge Management (JIKM) UiTM

URL: https://ir.uitm.edu.my/id/eprint/65775/

Abstract:

The rise of Big Data has inspired business organizations to venture into Big Data Analytics, however academic research and empirical evidence about the business value remains scarce. This paper attempts to evaluate the readiness of Malaysia companies in taking advantage of Big Data adoption. The research finds a great interest about Big Data Analytics (BDA) solutions that fuel with sound decision-making and influence organizations into growth mindset. Big Data provides various advantages to organization that would seriously consider all its perspectives alongside its lifecycle in the pre-adoption or implementation phase. The research attempts to outline the different aspects of Big Data as a management practice to leverage the values of Big Data adoption in future organizations. As for the underpinning theory, the technology organization-environment (TOE) framework is chosen to describe the organizational adoption towards innovation decisions and Resource Based View to manage the upskill of the workforce. This is of great interest to researchers, professionals, and policy makers.

APPENDIX 8

RESEARCH ARTICLE #2

Title of Article: Assessment of Data Quality Dimensions influencing Big Data Analytics role in Sustainable Development Growth Performance

Publisher: www.gbse.my

Year published: 2024

Volume: Volume 10

Page: 94-104

Issue: 28

Name of Journal: Journal of Global Business and Social Entrepreneurship (GBSE)

URL: http://gbse.my/V10%20NO.28%20(JAN%202024)/Paper-347-.pdf

Abstract:

Many nations are increasingly interested in the value of massive amounts of data, driven by the growing importance of Big Data Analytics (BDA) in today's competitive landscape. The adoption of Big Data Analytics enables organizations to strategically enhance their operations efficiencies, gain a competitive edge, and sustain long-term growth. In the context of Sustainable Development Growth (SDG), ensuring high data quality becomes even more critical, as decisions based on inaccurate or incomplete data can lead to suboptimal outcomes and potentially adverse environmental or social impacts. Prior research on Big Data Analytics has ignored data quality in favor of adding more Big Data attributes – referred to as Vs (volume, variety, velocity, etc.) Poor quality, outdated, and incomplete data can result in inadequate decision-making. Therefore, the primary aim of this study is to explore the importance of Data Quality Dimensions (DQD) and Big Data Analytics adoption can influence the effective impact measurement and data collection for the success of SDGs. Key variables from research literature reviews were incorporated into the research framework for this study. This study used quantitative method of cross-sectional survey to data professional practitioners and management board (senior and middle managers) that involved in Big Data Strategies within Malaysia. By introducing novel insights in the realm of Big Data Analytics, this study contributes to the body of literature and serves as a valuable resource for future scholars and industry practitioners who wish to investigate BDA solutions associated to performance of SDGs.