A Study on the Drivers and Barriers for the Business Intelligence Adoption

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DECLARATION

I hereby declare that:

(1) This MKMA 25106 Research Project is the end result of my own work and that due acknowledgement has been given in the references to all sources of information be they printed, electronic, or personal.

(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) The word count of this research project is 24,779.

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ABSTRACT

In Malaysia, overwhelming of data and information is enforcing the adoption of Business Intelligence (BI) to support decision making in order to achieve competitive advantage. In the extent of BI adoption, there are many factors influencing the BI implementation success which are important information to the enterprises. This study seeks to identify the common drivers and barriers for BI adoption as a guideline prior to implement BI in an enterprise. In this study, the model of technologies-organisation-environment (TOE) was adapted to delineate the drivers and barriers of BI adoption where the measurement of BI adoption was based on its core functionalities such as reporting, statistical, decision making, forecasting and KPI. The study methodology was then extended through the quantitative method by designed a questionnaire and distributed to respondents who working in Malaysia in order to collect primary data for analysis. Subsequently, the data collected was analysed with selected multivariate data technique to identify the significant BI factors against the adoption. The research reveals only minor drivers and barriers have significant relationship with BI functions adoption based on analysed results where most of the drivers are derived from organisation compare to technologies and environment.

CHAPTER 1

INTRODUCTION

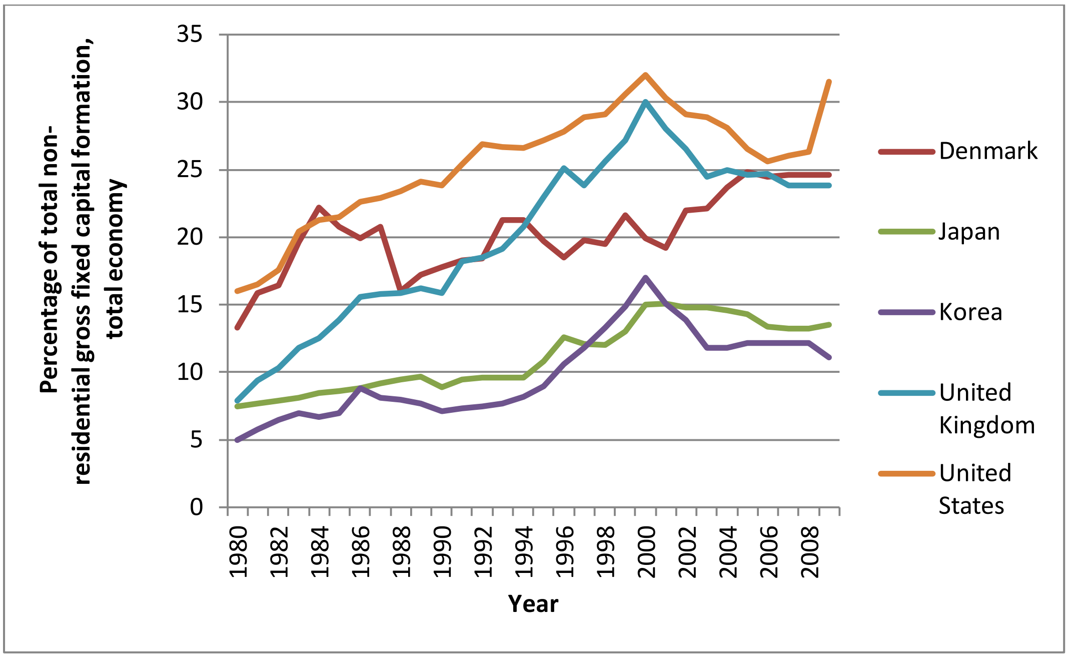
This chapter begins with an overview, historical background and development of Information Technology (IT) and Business Intelligence (BI) in Malaysia. Given the growth of the BI importance, the significant drivers and barriers towards BI adoption critically necessitate to be determined. This research project provided an opportunity to analyse the BI adoption level in Malaysia and identify the respective drivers and barriers at the same time to benefit the corporate in making decision for BI adoption. Prior to research literature and analysis, the research questions, justification, scope and overall outline were formulated in the following sections.

1.1 Background of the Research

In highly competitive markets, successful companies are differentiated by their ability to make accurate, timely and effective decisions in addressing the customers' preferences and priorities (Bose, 2009). Increasingly, intensity of Information Technology (IT) usage was witnessed over the needs of business (Kursan & Mihic, 2010). In order to gain competitive advantage over competitors, companies have stated the information systems investment to renew and improve business processes (Rajteric, 2010).

According to Organisation for Economic Co-operation and Development [OECD] (2010), the Information Communication Technology (ICT) investment was increasing significantly from year 1980 to 2009 internationally. The incremental trends in ICT investment have shown in Figure 1 for five (5) countries, namely Denmark, Japan, Korea, United Kingdom and United States. These countries had scored the high increment from the range of 80% to 201% where United Kingdom owned the highest (201%) and Japan has the lowest (80%).

Figure 1: Share of ICT Investment in Non-residential Gross Fixed Capital Formation (1980-2009)



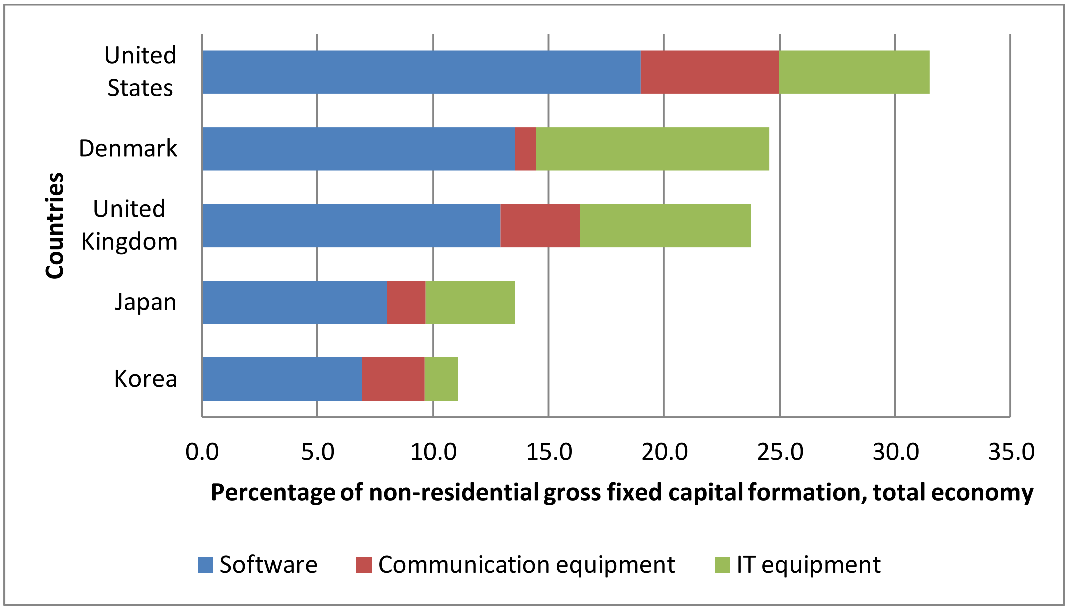
Note. Adapted from *OECD Factbook 2010 Economic, Environmental and Social Statistics.* (2010). OECD Publishing and *OECD Science, Technology and Industry Scoreboard, Investment in ICT.* (2011). Retrieved Feb 19, 2012 from http://www.oecd-ilibrary.org/sites/sti_scoreboard-2011-en/02/08/index.html?contentType=/ns/Chapter,/ns/StatisticalPublication&itemId=/content/chapter/sti_scoreboard-2011-19-en&containerItemId=/content/serial/20725345&accessItemIds=&mimeType=text/html

As defined in OECD (2008), ICT investment is referring to the acquisition of equipment as well as computer software utilised in business production or operations at least one (1) year. These investments are categorised into three (3) major components as listed below.

1. IT equipment (computer and related software)
2. Communications equipment
3. Software (acquisition of pre-packaged software, customised software and develop in-house software)

As shown in Table 1, the software component was contributed more than 50% from overall ICT investment in year 2009. These figures represents the software is embraced an imperative role in the corporate world.

Figure 2: ICT investment by Asset in OECD 2009



Note. Adapted from *OECD Factbook 2010 Economic, Environmental and Social Statistics.* (2010). OECD Publishing and *OECD Science, Technology and Industry Scoreboard, Investment in ICT.* (2011). Retrieved Feb 19, 2012 from http://www.oecd-ilibrary.org/sites/sti_scoreboard-2011-en/02/08/index.html?contentType=/ns/Chapter,/ns/StatisticalPublication&itemId=/content/chapter/sti_scoreboard-2011-19-en&containerItemId=/content/serial/20725345&accessItemIds=&mimeType=text/html

Table 1: Percentage of ICT Investment Asset in OECD 2009

ICT Category	Korea	Japan	United Kingdom	Denmark	United States
Software	62.55%	59.37%	54.39%	55.07%	60.34%
Communication Equipment	24.37%	12.27%	14.53%	3.79%	18.92%
IT equipment	13.07%	28.37%	31.07%	41.14%	20.73%
Total	100%	100%	100%	100%	100%

Note. Adapted from *OECD Factbook 2010 Economic, Environmental and Social Statistics.* (2010). OECD Publishing and *OECD Science, Technology and Industry Scoreboard, Investment in ICT.* (2011). Retrieved Feb 19, 2012 from http://www.oecd-ilibrary.org/sites/sti_scoreboard-2011-en/02/08/index.html?contentType=/ns/Chapter,/ns/StatisticalPublication&itemId=/content/chapter/sti_scoreboard-2011-19-en&containerItemId=/content/serial/20725345&accessItemIds=&mimeType=text/html

In past decades, Malaysia government had played his role in developing IT competitiveness of human assets by providing facilities in schools, tax exemption, developed Multimedia Super Corridor (MSC) flagship project and other ongoing projects (Malaysia Information Technology Report Q4, 2011). More international vendors of software, hardware and IT services were brought into Malaysian market to introduce the robust technologies from oversea.

The government efforts had boost up the IT investment in past few years and expected to be increased more in the future. In 2010, the investment solely for computer hardware was RM9.1 billion (US$2.4 billion) and expected to reach RM9.9 billion (US$2.6 billion) in 2011 (Malaysia Information Technology Report Q4, 2011). In other hand, software business in Malaysia did not do well in 2010 because of business recovery from economy crisis but expected to achieve RM3.0 billion (US$805 million) in 2011. The paper also had forecasted a rise on hardware and software investment in 2015 which are RM13.4 billion (US$2.9 billion) and RM4.6 billion (US$1.2billion) respectively.

Table 2: IT Investment (millions of dollars) in Malaysia

IT Investment	2011 (Actual)	2011 (Forecasting)		2015 (Forecasting)	
	In RM million	In RM million	Growth (%)	In RM million	Growth (%)
Hardware	9.1	9.9	8.8%	13.4	35.4%
Software	-	3.0	-	4.6	53.3%
Total	**9.1**	**12.9**	41.8%	**18.0**	39.5%

Note. Adapted from Malaysia Information Technology Report Q4, 2011

The needs to achieve the operations automation and productivity increment were also the core factors in encouraging a corporate to adopt the IT applications. Hence, the backbone applications such as Enterprise Resource Planning (ERP), accounting and human resource had increased their popularity in the corporate world (Malaysia Information Technology Report Q4, 2011). Besides, Malaysia government announced a two-year extension on import tax and sales tax exemption on broadband equipment (Malaysia Information Technology Report Q4, 2011). This exemption was also successfully stimulated the implementation of web application which requires internet access as a primary requirement.

This new trend also was supported by Small Medium Enterprises (SMEs) in Malaysia where their corporate strategy had extended from expanding markets share to seeking higher efficiency in managing their business and productivity. In additional, the introduction of flexible payment schemes based on deliverables and the growth of local software providers had make the IT application implementation more affordable. Consequently, the software demands are projected to have significant increment in the coming years.

Indeed the various IT application implementation were getting trendy in business world, hence the data input to capture the business operations and productivities was respectively increased. In order to simplify the data input and reduce the man-powers, the application trends were rapidly extended from the information capturing to system integration to avoid work duplication. Nevertheless, this IT evolution was still insufficient to achieve business competitive advantage as the executives were facing problems to making decision by retrieving information from overwhelming data (Lonnqvist & Pirttimaki, 2006).

Increasingly the demands of information process and sharing, therefore the development on advanced analytical tools were established. The advanced analytical is known as a technique to combine the past information upon circumstances, present events, and projected future actions which essential to business decision making (Bose, 2009). Simultaneously, the technologies on hardware and networking also heighten up in order to support them. Data warehouse was introduced to gather all the data from their sources database and perform the data integration by applying the defined rules. The new technique of data mining, On-line Analytical Processing (OLAP), is used widely in processing tonnes of data in data warehouse and proceeding to reports generation

Definitely an advanced analysis tool is not used alone; it groups the different techniques together as a whole to perform data analyses to answer questions or problems. These combined advanced techniques, more commonly known as Business Intelligence (BI), derived as a software solution to provide supportive information for decision making in various level of business process. The main components of a BI system are inclusive of integration, aggregation and multidimensional analysis of data origination from various information resources.

As a developing country, Malaysia also went through the same IT evolutions as other countries. Currently, the need of BI system in corporate is widely increased with the intention of overcome the constraints of backbone application. Software-as-a-Service (SaaS), a well-known BI software had achieved a double-digit regional growth in Malaysia as a solid proof of the BI adoption boost up which was reported in Information Technology Report Q4 (2011).

Like any other IT application, the justification on return of investment for BI system was intangible and tough to be measured. Although the need of BI system is significant to the corporate, but it is a challenge for executive to convince the management and shareholders. Moreover, there is no proper guideline or relevant information provided to assist executives when they are facing the challenges and obstacles. Hence, there is a necessity to conduct a research study to identify the significant drivers and barriers to BI adoption.

1.2 Problem Statement

Undeniably BI has become more essential in today businesses in order to enhance the decision-making process, subsequently to gain the competitive advantages in the market. Hence, the BI adoption level in Malaysia is essential to be disclosed with a proper research study. However, the present researches only emphasised the adoption level either in general or ERP application. By having the information pertaining to BI adoption level, the awareness will be built among the Malaysia corporate.

Although there were many literatures being studied on BI, there are less information pertaining study to the extent of the drivers and barriers in implementing BI especially in Malaysia business climate. Without this information, the executives were having a tricky time to prepare the related proposal as well as persuade the top management in order to implement BI across the corporate. Therefore this research study outcome will provide a valuable guideline in line to promote BI in Malaysia.

BI considered as a new technology and is becoming a necessity application in Malaysia corporate. Moreover, the investment on BI is high due to the needs of licensing purchase, implementation costs and infrastructure. Although there was a growth of local system providers in BI which able to reduce the implementation costs, but their stability and comprehensiveness still far away from international software. Therefore, executives urged to perform an assessment and research in term of investment costs and system feasibility against all the existing alternatives in the market. The exposure on BI drivers and barriers will minimise the research scope to be performed by executives and increase the probability to be accepted by corporate.

1.3 Research Questions

The following research questions were formulated which expected to be responded at end of this research study.

1. What are the BI adoption levels in Malaysia?
2. What are the correlation between BI adoption and driver/barriers of implementing BI in Malaysia?
3. What are the significant drivers and barriers of BI adoption in Malaysia?

1.4 Research Objectives

Ever since BI tool was used to deliver an efficient business decision-making, it is vital for an enterprise to implement BI successfully across various working levels. The efficient levelled business decision-making together with supportive quality information are affecting every single aspect of business operations with a target of maximising the business profits. However, a proper research and feasibilities study need to be completed by executives or project team prior to system implementation. This study also can be used to convince the shareholders or board in order to approve on it.

This research project is to determine the drivers and barriers of implementing BI in Malaysia thus the association with its adoption level in this area. To ensure objectives of study being achieve, the objectives were formulated as follows:

1) Identify the BI adoption levels in Malaysia.
2) To analyse the correlated between BI adoption and drivers/barriers of implementing BI in Malaysia.
3) Identify the significant drivers and barriers of BI adoption in Malaysia.

1.5 Justification for Research

As discussed in the background of research, Malaysia IT investment was growing in past few decades to automate the business process and increase the operations efficiency (Malaysia Information Technology Report Q4 2011). Despite of decreasing of hardware price and increasing of business demand, more enterprises were willing to invest into traditional application such as Enterprise Resources Planning (ERP) and consequently derived the situation of data overwhelming. Many executives were complaining they are data-rich but information-poor when they need to make business decisions (Computer Economics, 2008). To overcome this problem, corporate needs a crucial application system to support in making correct and timely business decisions by having reliable, accurate and punctual information (Rajteric, 2010). Therefore, enterprises have started to implement advanced analytics application which is a combination of various tools to gain information, perform analyses, and predict the outcome.

According to technology trends, many Malaysian enterprises had been consider BI, a well known advanced analytical tool, where 60% of overseas corporate was invested on it in 2008 (Computer Economics, 2008). Although the BI is proven to be essential for management effectiveness, the executives and managers were facing a difficulty to demonstrate or obtain the positive return on BI investment which concerning the shareholders the most (Computer Economics, 2008). Given its initial high implementation costs and significant change in business processes, supports from management and shareholders are even tougher. Additional, the promise of cost reduction and revenue increase cannot be achieved unless the BI is successfully adopted within an organisation (Bose, 2009).

The research study of drivers and barriers to BI adoption in Malaysia could be a useful reference for any business executives and IT managers in order to convince the management for BI implementation. With significant proven results on the advantages, the confidence level of management towards BI investment will be increased and also it will boost up the BI adoption level. In contrast, the obstacles that defined in the research will become an important guideline in risk analysis while management justifying the BI implementation. The significant impact of drivers and barriers towards the level of adoption which identified in research is supporting enterprises to make more accurate decisions on BI implementation. This also will assist corporate to be aware of the significant barriers and should overcome them prior to BI implementation towards successful.

In the market, there were many researches pertaining adoption levels on ERP or IT conducted but limited on BI adoption level. Therefore, this research is also providing the current state of BI adoption level in Malaysia with a small scale of data. This research could be expanded to a large scale of data by using the same structure to derive more accurate results.

1.6 Outline of the Thesis

This research project is contains the following five major chapters:

Chapter 1 Introduction: briefs the background of research include current state of Malaysia's IT and BI. Then it continues with discussion of current problem faced and necessity of BI to overcome it. The justification of the research and study contribution have discussed here by support of researches and articles. Lastly the research objectives were identified here to ensure the research achievement.

Chapter 2 Literature Review: includes extensive literature review of historical development of IT and business decision-making in Malaysia. Then it narrows more to contemporary literature which reflecting theories on advanced analytical tools and BI. The views and opinions of researchers concerning a broad spectrum of theories and approaches are discussed in details.

Chapter 3 Research Methodology: explain how the research was conducted, research framework to developing primary data collection process, and research approaches. The discussion on variables used in this study and development of hypotheses will be presented at this chapter.

Chapter 4 Research Findings: presents the descriptive statistics of data collection of this study, it then continues to describe the statistical analysis used to evaluate the hypotheses established.

Chapter 5 Discussion and Conclusion: presents the discussion of the research findings, presents a quantitative analysis of result with supportive data, result comparison with other researchers, suggests conclusions and study implications. It also discussed on limitation of the research study conducted.

CHAPTER 2

LITERATURE REVIEW

This chapter includes studies, writings and opinions pertaining to current state of IT in general and specifically in Malaysia. It also discusses the contemporary research of organisations decision-making process, application systems used to support decisions making, and lastly the development of BI. This literature review provides the necessary background in order to understand the forces shaping the BI adoption level. The broad spectrum of theories and approaches are discussed in details to form the conceptual framework for this research study.

2.1 IT in Business

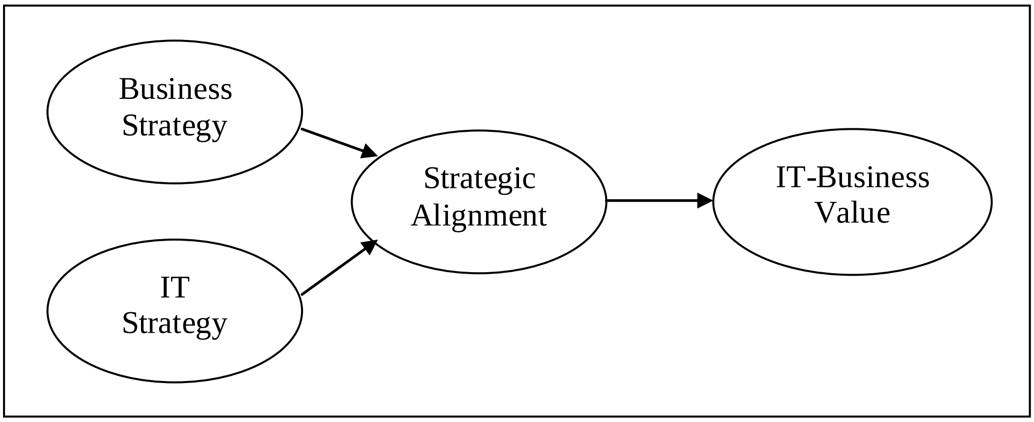
IT has become an essential element in business processes when the organisations started their expansion towards internationalization. Towards received the maximum benefits from technologies, the IT implementation and business strategies need to be aligned (Luftman, Bullen, Liao, Nash, & Neumann, 2004). As refers to Deudahi, Andersenm and Sein (2005), the alignment is the extent to which the IT is supported by business strategies.

A positive relationship between IT investment and firm performance is proven in the research of aftermath of the productivity paradox (Kohli & Devaraj, 2003). In this research, the strategic alignment, which defined as relationship or fit, linkage, harmony and integration between IT and business strategy, is a key component in search for greater value from IT (Tallon, 2008). The strategic IT alignment affects the profit, productivity, sales growth, and reputation which repeatedly establish in the studies. This was encouraging enterprises to consider the additional efforts to extend the level of robust between IT and business strategy (Tallon & Pinsonneault, 2011).

To achieve the strategic IT alignment, executives' competencies and skills are essential in order to embed IT into business processes. With the deep understanding on IT's capability to improve business process, executives could champion an IT project with assistance of IT manager in an organisation (Deudahi et al., 2005).

Identifying the key processes by organisations where alignment between IT and business strategy should be tight in turn drives IT business value within the process (Tallon, 2008). The process level research model proposed by Tallan (2008) is presented in Figure 3.

Figure 3: Conceptual Model for the Alignment of Information Technology and Business Strategy



Note. From Tallon, P.P. (2008). A Process-Oriented Perspective on the alignment on Information Technology and Business Strategy. *Journal of Management Information Systems, 24 (3),* 227-268.

2.2 IT Investment

Today, the business processes have constantly adjusted to overcome the rapid change environment and also IT advances in order to gain competitive advantages (Lee, 2004). With IT supports, managing the external value from business processes is effortless to generate value added for organisations which is crucial for an enterprise's success. Hence, a favorable plan of IT investments to support business processes execution always is a top priority by business executives (Neubauer & Shammer, 2007). Unfortunately, a poor IT investment decisions may lead to a corporate failure with low morale of executives.

The IT investments process virtually still being inconsistent in majority corporate practices (Ward & Peppard, 2002). By refers to Cooke and Parrish (1992), 70% of organisations have discovered there was no formal justification and post-implementation review processes. Among the evaluation performed on IT investment, more than 50% of the cases have used financial analysis techniques which are inappropriate for IT project (Ward & Peppard, 2002). The financial analysis techniques do not cover the overall risk analysis required for IT project to provide accurate assessment.

An irresistible number of existing IT systems that ready for implementation and set continues to grow (Adomavicius, Bockstedt, Gupta & Kauffman, 2008). Moreover, the size and complexity of IT background contributes to the difficulty of forecast future IT expansions. Definitely the decision making and justification for IT investments are the important strategic in an organisation but it is tricky for the executives even the most-knowledgeable in presence of technological, organisational and market complexity (Bacon, 1992).

An IT investment decision can be described as a complication and multistage processes involving a variety of actors at different levels within an organisation (Bower, 1970). During the process of sequence actions with begins of crisis or problem identification and opportunity of IT project approval, organisational actors can exercise their power to influence the final decision (Boonstra, 2003).

Hence, an accountability framework for IT investment decisions was established as IT governance to ensure the outcome aligns with organisation's overall vision and goals.

2.3 Application System Trends

In 1960s, the application industry was still underdeveloped where the application development was leading to improve the transaction processing systems by in-house programmers (Mcnurlin & Sprague, 2006). The application development remained at the purview of Information Systems (IS) managers and IS managers might looking at existing applications in the market occasionally.

Subsequently, the application development was improved to apply modular and structured programming techniques such as Computer-aided software engineering (CASE) and object-oriented programming (Cox & Novobilski, 1991). Later, this development was expanded to life cycle development methodologies and software engineering. During this stage, the system prototyping which refers to quick development of a mock-up system become more well-known.

The purchased software soon became an alternative to organisations and IS managers also began their interest in the other applications other than transaction processing. The other applications such as decision support systems (DSS), report generation and data inquiry soon shifted from programmers to end users.

Application trends were move towards the open systems environment and enterprise resource planning (ERP) systems. The open systems continue to demand various products work together where ERP was integrate functions of an organisation tightly to replace the legacy systems. During this stage, ERP has become the foundation information system for the large corporations where medium companies commented the implementation so expensive (Buckhout, Frey & Nemec, 1999).

In the mid-to-late 1990s, use of the Internet by businesses was beginning a revolution in the use of IT (Mcnurlin & Sprague, 2006). The organisation strategies were changed to utilise the Internet to conduct businesses. Therefore, the application was becoming more netweork-centric and moves the application from being decentralised to being centralised. The web services was a significance proven of moving application and programming to real network centric (Hagel & Brown, 2001).

2.4 Business Decision Making

The business environment is becoming more and more complex every day. The intensity of business environment factors such as market, consumer demands, technology, and society has increases with time and leading to more pressures and more competition (Turban, Sharda, & Delen, 2011). Therefore, the managers must respond quickly, innovate and be agile to survive in this kind of environment. Ultimately, the fast-changing business environment often requires faster decision from managers, which may actually be unfavorable to decision quality.

Mintzberg (1980) prevails the managers required perform three major categories tasks such as interpersonal, informational and decisional. Among these categories, the toughest tasks facing by managers are making decisions based on their experience and judgment. Decision making is defined as a process of choosing two or more alternative courses of action (solutions) for the purpose of attaining one or more goals (Turban et al., 2011). In the old times, managers considered decision making is a talent acquired over a long period through experience and based on creativity, judgment, and intuition. However, the recent research has shown managers are more consider methodical, thoughtful, analytical decision making tend to outperform those with strengths in interpersonal communication skills (Brooks, 2009).

In making decision, a five-step process is commonly applied by managers with added a new step by management science as described below (Turban et al, 2011).

1. Define the problem
2. Classify the problem into a standard category
3. Construct a model that describes the real-world problem
4. Identify the possible solutions to the modeled problem and evaluate the solutions
5. Compare, choose and recommend a potential solution to the problem

By refer to the decision making process, it is obvious that managers required the related and sufficient information being provided prior to derive alternative solutions. Information is valuable and critical to managers as the basis of decision making and act as medium to coordinate its activity (Jordan & Ellen, 2009). However, the transaction data processing systems only emphasise on data capturing across the organisation but incompetence to extract valuable information from millions of data. Consequently, when data continues to grow, managers are facing onto a problem of data overwhelming and lead to the difficulties of making decision.

Informational needed has led changes in decision-making processes in corporate (Hocevar & Jaklic, 2010). Managers start seeking well supported information for decision making instead of rely solely on intuition to preserve the competitiveness of corporate. Reliable systems are urgently requisited by organisations to enable analysts and access to information related to quality decision-making (Puklavec, 2001).

High quality of decision making includes accuracy, timeless and clarity after processed by an information system. In addition, difference between values of a good or bad decision is based on information which shows the impotency of good information (Bose, 2009). Thomsen (1997) has disclosed the greater difference between the effects of good and bad decisions, the greater importance of access to quality information.

2.5 Advanced Analytical Techniques

In order to achieve the business goals within the high competitive markets, the organisations gain control over the business decisions by integrating advanced analytics (Apte, Hong, Natarajan, Pednault, Tipu & Weiss, 2003). The advanced analytics driven data analyses allow organisations to have a 360 degrees view of their business operations and customers to direct, optimise and automate their decision making. It results in successful organisational goals achievement, increased of cross-sell revenue generation, decreased costs, reduction in fraudulent behavior or increased of promotional campaign response rates depends on business strategies (Bose, 2009).

In general term, advanced analytical is simply mean applying various advanced analytical techniques with group of tools to gain information, analyse information and predict outcomes for answering questions or solve problem which incurred (Bose, 2009). The common advanced analytics used in the market is statistical analysis to trace the data trends and patterns by gathering more information. Other techniques involved are fuzzy logic to manipulate incomplete data and neural network to manage predictive analytics for outcome (Wu, Li, Bot & Chen, 2006).

Data integration and data mining are the basis for advanced analytical tool to gather information and data integrate for pattern recognition and relationship identification (Wang & Wang, 2008). The new trends of data mining such as text mining and web mining have improved the corporate performance and customer data in the textual form (Fan, Wallace, Rich, & Zhang, 2006). Text mining relies on sophisticated text analysis techniques that distill information from free-text data where web mining is to discover patterns from web contents, structure and usage (Oliveira, Loh, Wives, Scarinci, Musa, Silva, & Zambenedetti, 2004).

The dio-mining is a combination of data mining and text mining which has proven valuable in banking and credit card customer relationship management (Feldman & Sanger, 2007). Besides structured data in transactions, this technique can includes the call logs associated with customer service and customer spending patterns. Another text mining application, electronic discovery, has significant gratitude from civil litigation to assist in organising electronic files using the attached metadata (Volonino, 2003).

The challenges with advanced analytics encountered are the well supports from organisational, managing implementation, ease of use for users and data sharing availability (Bose, 2009). The successful implementation of advanced analytics needs the involvement of functional team, appropriate processes in project and incentives to give motivation which failed to be achieved by most of the organisations. The approach selected to implement an advanced analytics needs to be managed carefully to avoid low morale and excessive finger-pointing. In addition, it is not an easy technology for end users to understand or use the advanced analytics, hence corporate may not utilise up to its fullest potential. The advanced analytics required appropriate data or high quality data to be performed effectively, but the data sharing across organisation is a challenge to maintain their privacy and confidential.

2.6 Business Intelligence (BI)

2.6.1 Decision Support System

As technology evolved, new computerised decision support application were developed over years by using multiple frameworks. The history of DSS can be organised into five broad categories including communications-driven, data-driven, document driven, knowledge-driven and model-driven decision support systems (Power, 2004).

In 1970s and 1980s, the concept of decision support systems (DSSs) evolved to take over complex decisions completely or support executives who need to make the complex decisions (Mcnurlin & Sprague, 2006). There were two types of computer support for decision making derived which are management information systems (MISs) and operations research/management science (OR/MS). MISs provides reporting whether based on standard well defined format or ad hoc requests and ability to query the data where OR/MS used mathematical models to analyse and understand specific problems.

Sprague and Carlson (1982) have defined the DSS as below.

1. A computer-based systems
2. System that helps decision makers
3. Systems that confront ill-structured problems
4. Systems through direct interaction
5. Systems with data and analysis model

These definitions were supported by Gorry and Scott-Morton (1971) who defining the DDS as an interactive computer-based system which assist decision makers utilise data and model to solve unstructured problems.

An early framework for computerized decision support was proposed by Gorry and Scott-Morton (1971). The framework is a 3-by-3 matrix with two dimensions of degree of structuredness and types of control. Based on Simon's idea (1997), decision making process fall from the range of highly structured to highly unstructured where type of control are range from operational to strategic planning. This idea improved the decision making process into phases as shown in Table 3.

Table 3: Decision Making Process

No	Phase	Description
1.	Intelligence	Searching for conditions that call for decisions
2.	Design	Inventing, developing, and analysing possible solutions
3.	Choice	Selecting a course of action from available choices
4.	Implementation	Adapting the selected course of action

Note. From Turban, E., Sharda, R., & Delen, D. (2011). *Decision Support and Business Intelligence Systems (9th ed.).* New Jersey: Person Education, Inc.

The types of DSS can divided into two major categories inclusive of model-oriented and data-oriented (Turban et al., 2011). The quantitative modules are using in model-oriented DDS to generate a recommended solution to a defined problem. On other hand, data-oriented DDS has provided assistance in ad hoc reporting generation by applying the defined business rules.

As proven by businesses, the computerised DDS has offered quality and agile supports to the organisations with timely computation and improved data management (Turban et al., 2011). The productivity of organisations indirectly improved with the speedy communication and collaboration. The giant data warehouse where having cognitive limits in processing and storing information also overcome by DDS. The DDS with web services also allows access DDS from anywhere through internet.

When the demands grew from business, the new technologies of On-line Analytical Processing (OLAP), data warehousing, data mining, and intelligence systems were introduced as an improve efficiency in decision making. These new technologies started appear under the names of Business Intelligence (BI) and business analytics in mid-1990an.

2.6.2 Business Intelligence

Business Intelligence was introduced by the Gather Group in the mid-1990s (Turban et al., 2011). This was derived from the early concept of MIS reporting systems in 1970s. The reporting systems were static with two dimensional and led to emerged of executive information systems (EIS). Some capabilities introduced were dynamic multidimensional reporting, forecasting and prediction, trend analysis, drill-down to details and others. In the mid-1990an, these capabilities with new ones appeared under the name of Business Intelligence (BI).

In 1989, the BI was used as a common name to describe the concepts and methodologies for development of business decisions using facts and information from supporting systems by Howard Dresner (Power, 2007). Nowadays, BI is defined as a software solution to acquire right information for business decision-making by using technologies and methodologies needed (Kursan & Mihic, 2010). From business users' point of view, BI is a software tools that enable to see and use large amounts of complex data (Thompson, 2004). Another study unveils that BI is capturing, assessing, understanding, analysing, and converting one of the basic and most valuable assets of the company, represented by the raw data into quality information in order to improve business competition (Azvine, Cui, Nauck & Majeed, 2006).

In technical view, BI is an application or technology to gather, store, analyse and provide access to data to improve business decisions making process (Bose, 2009). To discuss further on BI history, summaries of BI evolution over the years to current state are diagrammatically captured in Figure 4 and each of stages was briefly discussed.

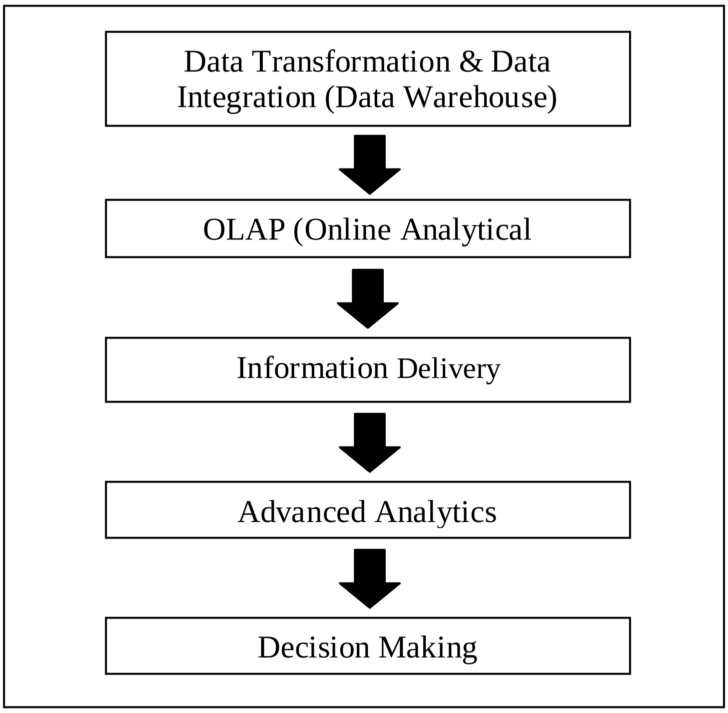
Rapid advances over several years in data capture, processing power, data transmission, and storage capabilities have enabled organisations to integrate various databases into data warehouses as data centralisation (Bose, 2009). The core of well-developed BI is the data warehouse which consists of two main components, data repository and metadata. Data repository a logical is collection of integrated information designed and gathered from many different operational data to support management decision-making. Metadata is data about data in simple definition to collect rules and directions that guide the extraction, transformation, cleansing, and loading data into data warehouse.

Technology of OLAP is typically used as query and reporting tools to effectively use to show historical data, but advanced analytics also start gathering attention such a more comprehensive approach to BI. Effective decision making to gain competitive advantage is driving the need for organisations (Bose, 2009).

As the recent forecasts, advanced analytics will be the driving force in BI market for some time. Majority organisations have built adaptive and embedded analytics over BI to sustain their competitive advantage and receive higher return on investment (ROI) (Bose, 2009).

Decision making process was improved by introducing embedded logic within analytic application with powered by business rules engine and predictive models (Bose, 2009). The logical conditions have been applied by business users into business rules engine to determine the case handling. Predictive models are identifying the most likely actions in probability throughout the history data to achieve the desired results.

Figure 4: Evolution of Business Intelligence



Note. Adapted from Bose, R. (2009). Advanced analytics: opportunities and challenges. *Industrial Management & Data Systems, 109(2)*, 155-172.

The four major components for BI solutions including data warehouse, business analytics, business performance management (BPM), and user interface (Turban et al., 2011). Besides the history data in summary, the data warehouse was improved to cater the current data to supports real-time decisions. Business analytics is a collection of techniques to manipulating, mining, and analysing the data in data warehouse. These techniques are fit into two major categories inclusive of (1) reports and queries, and (2) data, text and web mining and other sophisticated mathematical and statistical tools.

BPM, also referred as corporate performance management (CPM) is a portfolio of applications and methodology that contains BI architecture and techniques in its core. It holds the processes such as planning and forecasting of a business strategy. Dashboard and other information broadcasting techniques are using as the user interfaces. A wide-ranging visual view of corporate performance measures, trends, and exceptions can be displayed in dashboard by integrating information from multiple business area.

2.6.3 The Benefits of BI

The major benefit of BI to a company is the ability to provide accurate information when needed, including an up-to-date view of corporate performance (Turban et al., 2011). By using BI technologies and methodologies, business users enable to connect all business processes, and turned data into valuable information that enterprise based decisions upon. Companies need to get the right information to the right people at the right time in the right format so managerial can make decisions to improve enterprise performance ultimately (Bose, 2009).

Table 4: Definition of the Information

Important Points	Definition
Information	Not data that is important which these two terms are often used interchangeably. Data is the stored value and become information when supplemented by correct business context.
Right Time	Have information in hand at correct currency when decision is made.
Right Format	Way the information is presented – in high level trends or low level trends.
Right People	Insure right reports are distributed to the people who need the information to make decisions.

Note. Adapted from Jordan, J. & Ellen, C. (2009). Business need, data and business intelligence. *Journal of Digital Asset* Management, *5*, 10-20.

According to Thompson (2004), the benefits of BI as described in Table 5 based on an industry report, OLAP 3 which published on November 2003 by Nigel Pendse. This report is based upon a survey of around three thousand (3,000) peoples from one thousand and forty seven (1,047) user organisations and forty eight (48) countries. 81% of the companies agreed that the BI is generating more accurate reporting faster which is scored the highest among the benefits. Second highest scores for BI benefits is improved decision making which comprising 78% from the participants.

Table 5: Benefits of Business Intelligence (BI)

Benefit	% Companies Realizing Benefit
Faster, more accurate reporting	81
Improved decision making	78
Improved customer service	56
Increased revenue	49
Savings in non-IT costs	50
IT savings	40

Noted. From Thompson, O. (2004). Business Intelligence Success, Lesson Learned. Retrieve Apr 29, 2012 from http://www.technologyevaluation.com/research/articles/business-intelligence-success-lessons-learned-17547/

The statistics on benefits of BI are appear significantly more beneficial compare to other application such as ERP or SCM. However, the combination of ERP or SCM with BI is generating more benefits because ERP and SCM need BI tools to bring forward the most important aspects of the overwhelming data.

2.6.4 Challenges for Advanced Analytics Technologies / BI adoption

Advanced analytics is not an easy technology for users to understand or know how to use it but required intensive training and assistance from specialists (Bose, 2009). IT staffs and business managers required to be well trained to understand and utilise these systems. Therefore, the BI adoption is high possibility lead to a situation of implementing the technologies but lack of expertise to utilise the system to its fullest potential.

The outcome format is yet another challenge to advanced analytics technologies which needs to be simple and concise but the input normally immense high volume of data (Bose, 2009). Data warehouse design is a critical and tough stage to support BI solutions.

Data architecture is one of the challenges for BI which is result of not having common understanding of business terms. The business rules defined in the system impossible to fulfill the neither entire business areas nor departments requirements and derived a simple conclusion.

In different systems, the data is held differently and could be applied by different logic or data validation. This is known as 'different version of truth' across the corporation and derived conflicts within it. This was resulting by not having common business rules among the business areas and departments. In order to obtain insight data, the data integration on various sources is necessity but challenging.

During the implementation of Business Object (one of the BI software), the challenges faced by University of Illinoice including users training, reporting focus, use of BI tools and user buy-in (Wise, 2006). Expertise in the university needs to be trained to train end users and maintain the environment. However, the knowledge transfer from vendor to expertise often incompetence where in-house expertise with competence knowledge is not easy to be allocated.

The gap between reporting requirements from University of Illinoice and the Business Object's strength has brought in another challenge to the implementation. Business Object allows users to creating and deploying ad hoc reports and trending analyses where users required daily reporting generation. Besides, users' interest was remaining low to adapt the changes derived from the new application. This has increased the implementation duration to get user buy-in.

The data process of BI solutions was limited due to the limitation encountered in server environment. The server unable to process the huge volume of data efficiently and produced the results timely. This issue is limiting the benefits received from BI solutions.

2.6.5 Drivers

Based on Kenton's (2005) research, the summary of environmental factors drive the business intelligence adoption in the market is cited as following.

1. Government regulations
2. Information overload
3. Demand for accountability and metrics
4. Improve on competitive responsiveness

Government requires the corporate reporting to be more transparent and forcing business to have better systems for storing and retrieving the current and detailed information (Kenton, 2005). A key feature of BI, self-service reporting was recognised by BI industry expert to provide the tangible benefits such as timely decision making, reduce man-power costs, reduce time-wasting costs of reporting and data analysed by executives who need it instead of BI specialists (Weber, 2013).

The successful of adoption on transaction processing application such as CRM, ERP and SCM systems in organisations has increasing data volume in no time. The data analytics of BI tools are required by businesses to segregate, mine and analyse millions of data to get ready for business and market events timely. With this tehnique, the frustration of consumers' data will be reduced (Weber, 2013). The data-driven decision will return more consistent positive outcomes where accurate and up-to-date information can provide better forecasting.

During the economic recovery, businesses were forced to continue trimming budget while entailing greater accountability for single spending area. BI provides tools such as data-mining, analytics and scorecards to track performance metrics united directly to corporate strategic goals (Kenton, 2005).

With increasing of market competitive, customer demand and pricing pressure, businesses need to speed up their processes that support aggressive competitive strategies. The real-time information can eliminates delay on businesses processes and streamline management to have agile decision making (Weber, 2013).

2.6.6 Barriers

Indeed BI has providing significant benefits to organisations, but its adoption was not succeeding. A study prevails the wrong approach decided by management or IT department will lead to failure of BI adoption (Weber, 2013). The errors might made by IT to give all data access to users resulting different version of truth in reporting.

Data warehouse is the data source for BI solution to perform analysis and generate reports. Without or insufficient quality data, the BI adoption will be on a risk (OGC, 2002). Hence, the partitioning design on data warehouse required to be aligned with user requirements on BI tools. The isolation of data warehouse will be an obstacle to implement BI as it might not able to support the complex reporting or analysis (Weber, 2013).

In the absence of engaged governance into BI solutions, the implementation team will be treated as cost center and isolated without proper justification on the value contributed (Weber, 2013). The effective governance process required to be aligned across the BI activities to deliver sustainable solutions (Armstrong, Gallo & Williams, 2013).

The unavoidable risks for BI systems are large-scale and costly project which affects the entire organisation, IT environment, business processes, organisation culture and employees (Bajgoric, 2010). Additional costs that aren't easily recognised and hidden also will reduce the confidence level of stakeholders on the BI solution. This includes long term cost of unsustainable BI solution, cost of frustration, lost productivity and turnover period (Weber, 2013).

Confusing of BI terminology and unclear of value propositions are the constraints of BI adoption. If the management or stakeholders do not know well on the BI and the business value derived, they are definitely not willing to invest on it or conducive to success (Armstrong et al., 2013).

Gap between business and IT alignment is a challenge to be overcome by BI team to design and build based to business users' desire (Bajgoric, 2010). The gap can be resolved with appropriate processes and mutual expectations between the BI team and business users (Armstrong et al., 2013).

2.7 Theoretical and Research Framework

One of the established approaches in technology adoption research study entails indentifying the factors that impact the adoption decisions in organisations (Troshani, Rampersad & Plewa, 2011). This approach is also known as 'innovation configuration' where the factors can describe the organisation adoption outcomes (Fichman, 2004). The characteristics of generic innovation and organisational are the sturdy predictors of IT adoption by both individuals and organisations. (Jeyaraj, Rottman & Lacity, 2006).

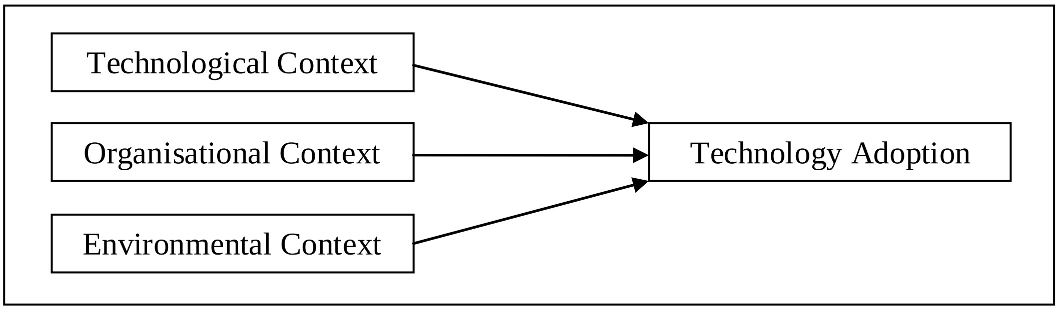
Adoption is defined as decision to fully utilise an innovation as the best course of action (Rogers, 1995). Primarily, innovation must be purchased, adopted and acquired by an organisation. Subsequently, it must be accepted by the ultimate users in the organisation called as implementation (Chong & Bauer, 2000).

In general, the motivations are lead an organisation to adopt an IT application. Based on an analysis performed, the categories of the motives quite similar among the research studies (Raymond & Uwizeywmungu, 2007). The motivations to adopt a technology basically can be grouped into environmental, organisational and technological which defined as techonology-organisation-environment (TOE) theoretical framework.

By refers to Tornatsky and Fleischer (1993), the theoretical framework of techonology-organisation-environment (TOE) was developed to explain the technology adoption and incorporation of information technology. There are three groups of predictors emphasised in this theory as briefed below (Baker, 2012; Raymond & Uwizeywmungu, 2007; Scupola, 2009).

1. Technological context represents the pool of existing technologies to a firm for adoption.
2. Organisational context refers the internal factors to an organisation influencing a technology adoption and implementation.
3. Environmental context defines as the external pressures in which an organisation conducts its business.

Figure 5: Theoretical Framework for Technology-organisation-environment (TOE)

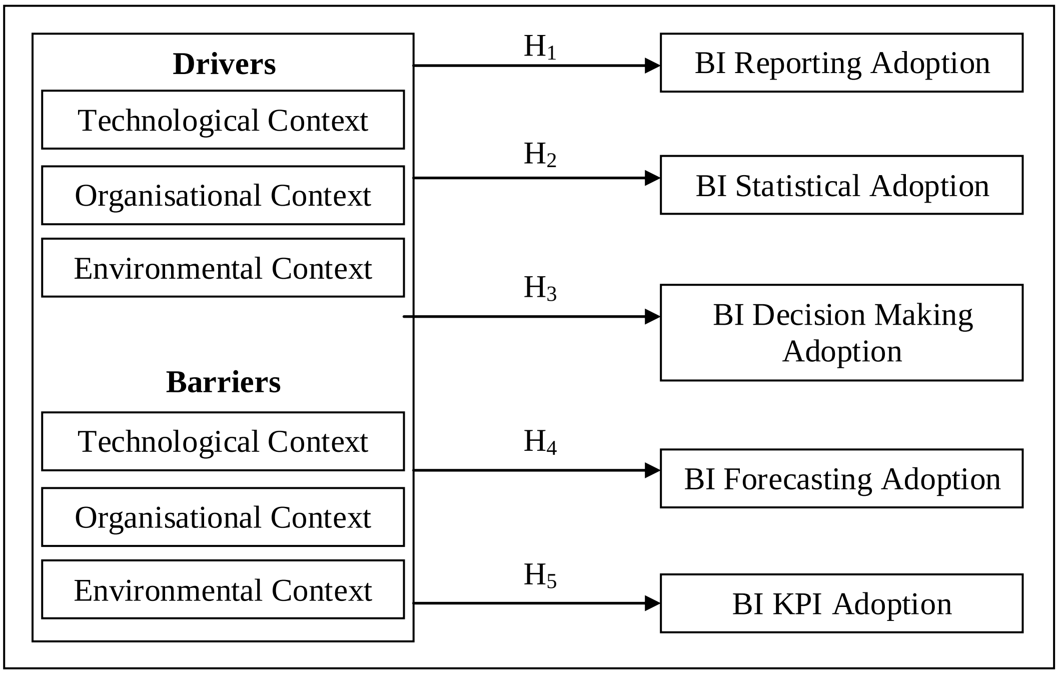


Note. From Tornatsky, L.G. & Fleisher, M. (1993). *The Process of Technological Innovation*. Lexington Books: Lexington, MA.

TOE theoretical framework was well accepted in the research studies conducted for technology adoption such as ERP, E-Commerce and green innovations adoption (Chieh & Yi, 2008; Raymond & Uwizeywmungu, 2007; Scupola, 2009). Hence, this framework was proven to have positive result from the testing of grouped factors with the respective technology adoption.

Since TOE was widely accepted and produced positive results, this research framework for BI adoption was developed by adapting from TOE framework as shown in Figure 6. The factors that encourage and reject BI adoption in an organisation will be derived from the three contexts as defined in TOE which are technological, organisational and environment. In other hand, the technology adoption was modified to be split into multiple adoptions based on BI modules. This modification on the TOE framework was targeted to have a research framework specifically for BI adoption by adapting its specification.

Figure 6: Research Framework for BI adoption



2.7.1 Technological

The needs of improving operation performance in an organisation are an important motivation to adopt technology (Oliver & Romm, 1999). These needs often derived from the limitation of existing systems where these systems failed to be efficiency and flexible (Dolmetsch, Huber, Fleisch & Osterle, 1998). This was the major motive of BI adoption in an organisation where the core systems failed to process data efficiently and produce useful information.

The decision to adopt a technology not only depends on the options available in the market, but also the fitting between the new technologies with the possessed technologies (Chau & Tam, 1997). The readiness of current systems for integration purposes as well as the infrastructure was the key obstacle to implement BI solution in an organisation. The investment cost to prepare an organisation for BI adoption is respectively high.

Besides, the other important factors in pressuring the adoption decision were perceived relative advantage, compatibility, trialability, complexity and observability of the technology innovation (Rogers, 1995). The benefits expected to be received when implementing a BI solution such as decision making across enterprise, reporting capability, data availability readiness and timely information. Non compatibility of BI system with current technology environment is one of the key barriers. Due to high costing for BI adoption, the capable to have a trail version of the system to be pilot tested will be part of consideration. Complexity of the BI adoption is considered high which involves technical knowledge in order to fully utilise the tools. Observability refers to the extent to which the expected benefits for BI adoption are obvious.

2.7.2 Organisational

The fit between the systems and organisation's processes was the head of the list of selection criteria (Everdingen, Hillegersberg & Waarts, 2000). Therefore, align the BI implementation with corporate strategies such as in resource allocation optimisation, improve overall enterprise performance, customer service excellence and others is essential.

The affordable cost of application and minimum of implementation duration are the essential consideration in making decision to adopt advance technologies (Ariss, Raghunathan & Kunnathar, 2000). Unfortunately, the investment costs for BI system is high and required longer implementation duration compare to other system.

2.7.3 Environmental

External pressure by its environment exerted on an organisation may result the system adoption. A case study shown a business depends on the technologies to control on the production costing tightly in order to achieve its business competitiveness (Dolmetsch et al., 1998).

The supply chain optimisation also is one of the factors that lead the system adoption (Raymond & Uwizeywmungu, 2007). With high demands from stakeholders, organisations required technologies to manage their operations and productivities.

Another essential environment context for technological innovation is the government supports throughout regulation (Scupola, 2009). The level of government involvement in fostering the technology adoption will either encourage or discourage it (Al-Qirim, 2006). Without government supports, the companies will lack of initiative to adopt BI system which burden their financial.

2.8 Empirical Studies

By referring to the research conducted by Ming and Woan (2008), the study was applied the technology-organisation-environment (TOE) framework to examine the factors that affecting the decision to adopt enterprise resource planning (ERP) in Taiwan's communication industry. In this study, four (4) out of eight (8) factors are proven to be the significant determinants against the ERP adoption based on the sample of ninety nine (99) firms in the industry.

A study has been carried out to examine the innovation management software adoption in an university of innovation commercialisation (Troshani et al., 2011). The in-depth interviews on sixteen (16) individual across the departmental functions were conducted to study the factors that shape the organisational motivations and capabilities by using the TOE framework.

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Despite of technology system, an empirical study on green innovations adoption among the logistics service providers was accomplished by adapting the TOE framework (Chieh & Yi, 2008). All the six factors examined were proven positively impacts on the intention to adopt green practices by analyzed one hundred sixty two (162) samples of questionnaire survey collected.

2.9 Hypotheses Formulation

Based on research framework, there are five hypotheses formulated to analyse the relationship between independent variables (BI drivers/barriers) and BI adoption.

2.9.1 BI Reporting Adoption (Hypothesis 1)

H_0: There is no significant relationship between BI reporting adoption and drivers/barriers.
H_1: There is a significant relationship between BI reporting adoption and drivers/barriers.

2.9.2 BI Statistical Adoption (Hypothesis 2)

H_0: There is no significant relationship between BI statistical adoption and drivers/barriers.
H_2: There is a significant relationship between BI statistical adoption and drivers/barriers.

2.9.3 BI Decision Making Adoption (Hypothesis 3)

H_0: There is no significant relationship between BI decision making adoption and drivers/barriers.
H_3: There is a significant relationship between BI decision making adoption and drivers/barriers.

2.9.4 BI Forecasting Adoption (Hypothesis 4)

H_0: There is no significant relationship between BI forecasting adoption and drivers/barriers.

H_4: There is a significant relationship between BI forecasting adoption and drivers/barriers.

2.9.5 BI KPI Adoption (Hypothesis 5)

H_0: There is no significant relationship between BI KPI adoption and drivers/barriers.

H_5: There is a significant relationship between BI KPI adoption and drivers/barriers.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the methods that used in this research in order to obtain data and information which comprises of primary data collection process, questionnaire design, data collection and qualitative approaches. In additional, this is followed by discussion on the variables and also derive of hypotheses with supportive of secondary data.

3.1.1 Research Design

Typically, researcher will use either qualitative or quantitative approaches to test the constructed hypotheses based on literatures. Qualitative data are collected by using unstructured in-depth interviews or observation on a focus group whereas quantitative data are in numbers which used to represent the characteristics or behaviors of an object (Hair, Money, Samouel & Page, 2007). Quantitative research also defined as a variables measurement for individual respondents to obtain scores that submitted to statistical analysis (Gravetter & Forzano, 2009). In order to provides summary information on multi drivers and barriers on BI adoption, quantitative approach was used in this research study. Trends of variables based on collected data also can be tracked easily compare to qualitative approach.

To facilitate the business problems studies, there are three type research designs such as exploratory, descriptive and casual design could be used by researchers (Saunders, Lewis & Thornhill, 2012). When a new relationship, pattern, idea or others need to be extended from a problem or opportunity, an exploratory research project will be chosen by companies (Sekaran & Bougie, 2010). The research is primarily to be applied in high innovative industries like Apple, Microsoft and Siemens (Cooper & Schindler, 2011). In order to test an event causes another, casual research is used to measure a change in one event bring outs a corresponding change in another event (Hair et al., 2007).

Descriptive research is to obtain data that describes the characteristic or behavior of the developed questions. It is usually structured and specifically designed to measure the characteristics which needed in this research study (Sekaran & Bougie, 2010). A questionnaire on BI adoption characteristics and drivers and barriers encountered during implantation was constructed in order to collect sample data from enterprises within Malaysia. Enterprises required filling up the demographic details such as age, gender, position, and IT annual budgets to facilitate findings assessment. This descriptive research is considered as cross-sectional which provide a 'snapshot' of the BI adoption level as well as drivers and barriers ranking in Malaysia's enterprises.

3.1.2 Sampling Approach

In the survey conducted, the population must be properly targeted in order to collect data from the peoples, events or objects that competent to provide correct response to the defined problems (Cooper & Schindler, 2011). The population defines as the group of people, events or things of interest which researcher wishes to study where the sampling refers to the method of selecting the right individuals for whole population (Sekaran & Bougie, 2010). Ideally the researcher would like to collect data from all members of a defined population which known as a census (Zikmund, Babin, Carr, & Griffin, 2010). However this is not feasible in majority of the researches to covers all the elements involved. Hence, a sample of the population is drawn using either probability or nonprobability procedures (Hair et al., 2007). Probability sampling involves a selection of a representative sample from the population using an indiscriminate procedure (Sekaran & Bougie, 2010). This is to ensure independence in selecting the sample which applied in this research study. Nonprobability sampling is to select the sample based on judgment in qualitative research.

The sample used in this study was drawn from employees in Malaysia's enterprises who explore to BI application in daily jobs. The employees' job positions are ranging from officer up to top management. These respondents were expected to answer the questionnaire concerning BI adoption level in their own enterprise thus providing information against the drivers and barriers of BI implementation. In order to ensure the objectivity in sampling, the target enterprises were ranging from small companies to big enterprise group in Malaysia. Data were collected from May 2011 to August 2011.

A sampling frame which defined as a complete listing of the targeted population was derived from Bursa website and internet. A total of eight hundred and twenty (820) listed companies in main board was targeted as the sampling frame for this research. Simple random sampling method was applied to select one hundred and fifty (150) companies from this sampling frame. The every fifth company in the list was selected until reached the target sampling. This sampling method is a straightforward way that assigns each aspect of the target population an equal probability of being selected (Cooper & Schindler, 2011). Therefore, this method has litter bias and offers the most generalisability compare to others. Unfortunately, it has disadvantage of non-accurate contacts information as well as the problem of refusals to participate the survey. Out of one hundred and fifty (150) chosen companies, there were only eighty six (86) respondents received with completed answers. By refers to Roscoe (1975), the sample sizes larger than thirty (30) and less than five hundred (500) are appropriate for most of the research. Hence, eighty six (86) respondents are considered appropriate for this research study.

3.2 Primary Data Collection Process

In quantitative data collection methods, there are three broad categories such as self-completion, interviewer-completion and observation (Sekaran & Bougie, 2010). Self-completion methods are referring to mail surveys, Internet or electronic surveys, drop-off or pick up, and other similar approaches. Interview-completed methods involve personal interviews with the respondents either face-to-face or via telephone (Cooper & Schindler, 2011). Observation studies require date collection in a large amount of numerical data in counting on behavior, actions or events (Hair et al., 2007).

Self-completion approaches were adopted in this research to facilitate data collection by using questionnaire. A structured questionnaire was designed to capture data from respondents with a predetermined set of questions. Key characteristics of individual respondents and companies pertaining BI adoption in respective company was scientifically measured through this instrument.

Electronic surveys were used with the rationale being of inexpensive, shorten the completion time, and produce high quality data. An electronic questionnaire was developed by using Google Docs with facility of storing data collected in Google spreadsheet. The greater flexibility gained was the questionnaires being located on the Google server which can include manipulations from respondents. Respondents were notified via email sent with the contents of hyperlink directly links to electronic survey and a proper cover page. This approach also enabled the global reachable and no interviewer bias.

3.3 Measurement in Research

Measurement is an important matter in business research prior to understand the business or concept. Without measurement, it is tough to make a statement on business behavior or phenomena. There are four levels of measurement which represented by different type of scales: nominal, ordinal, interval, and ratio (Saunders et al., 2012).

A nominal scale uses numbers as labels to identify and categorise objects, individuals, or events and not limited to two categories. Typically, nominal scales are used to identify individual, job positions, incomes, company's industry and other objects (Cooper & Schindler, 2011). Data analysis is restricted to the counts of responses in each specific category or percentage calculation for a specific question (Hair et al., 2007).

Rank ordered against the predetermined objects according to certain criterion such as preference, importance or age is referring to ordinal scale (Zikmund et al., 2010). This scale enables the researcher to compare if an object has more or less of a characteristic than other object but not to determine how much more or less (Saunders et al., 2012).

Rating objects or events by using numbers with equal distances between the numbers is defined as interval scales. Measurement of concepts such as perceptions, feeling, opinions, attitudes and values can be retrieved by using rating scales in business research (Cooper & Schindler, 2011). Rating scales commonly include the use of statements accompanied by precoded categories to indicate the extent of respondents' agreement or disagreement. More sophisticated calculation such as mean, median and standard deviation can be handled in data analysis.

Ratio scale possesses a unique origin or zero point in order to compute ratios of points on the scale. Examples of ratio scales are common weighing machines or bathroom scale with absolute zero points (Saunders et al., 2012).

Among the four levels of measurement scale, both nominal and interval scales were selected to identify the demographic, BI adoption level, drivers and barriers in adopting BI. A nominal scale was used to categorise the respondents through the data in demographic and BI adoption level which also classified as categorical scales. This nonmetric scale involves two or more response categories to allow this research can be more precise in measuring a concept.

The respondents’ agreement or disagreement on the statements pertaining to drivers and barriers in adopting BI was identified by using interval scales. This will facilitate the data analysis with more sophisticated computation. A five-point summated rating scale which is a metric scale was used to access the strength of agreement about a group of statements. It is commonly known as Likert scale which uses the scale individually.

3.4 Questionnaire Design

A questionnaire was developed based on the research objectives discussed in Chapter 1 and also literature conducted in order to conduct an effective survey. The questionnaire was initially developed based on the information gathered in literature review and evolved to meet the research objectives.

The questionnaire is designed to collect information pertaining to demographic of respondents and company, BI adoption level, drivers to BI adoption and barriers to BI adoption. All these information collected and interrelation between are critical in order to conduct effective discussion and analysis for this research.

3.4.1 Demographics

In section A, a few questions pertaining to demographic of respondents are provided in order to help the researcher to understand each respondent such as gender, age, position, and user type for BI.

In next section (B), information related to respondents’ company is needed in order to analyse the company’s characteristics which have impact on BI adoption. Respondents are required to provide the company information for IT-business initiatives, company industry and annual IT budget.

3.4.2 BI Adoption Level

Before begin the survey on key component of this research, understanding the current BI adoption level for each respondent's company is essential for researcher to compare with the company characteristics in section B and it also will be related to the key element of the research. This section (C) is asking the company's adoption level on reporting, statistical analysis, decision making, forecasting, and KPI.

3.4.3 Drivers and Barriers to BI Adoption

Drivers to BI adoption are listed in section D whereas barriers to BI adoption are listed in section E. Respondents were required to unveil the agreement level on each of the driver and barrier statement based on Likert scale range from 1 to 5 respectively represent strongly agree, agree, neutral, disagree, and strongly disagree.

The drivers and barriers were formulated based on characteristic of each category defined in research framework which was discussed in literature review. In summary, there were twenty eight (28) drivers and twenty (20) barriers statements pertaining to BI adoption identified and formed the Section D and E in the questionnaire.

Table 6: Summary of BI Drivers and Barriers based on Categories

Category	# Drivers	#Barriers
Technological	11	8
Organisational	14	9
Environmental	3	3
Total	**28**	**20**

3.4.3.1 Technological Drivers and Barriers to BI Adoption

The constraint of existing technologies in a business where it is unable to answer the functional needs will lead to motivate the adoption of BI application. The technological context can refers to data capability, application extension, reporting tools and the needs of business supports. Based on literature conducted, the eleven driver statements related to technological context had been identified.

Table 7: List of Technological Drivers to BI Adoption

Code	Description
T4	Enterprise wide data driven decision making capability
T5	Availability of data analysis tool
T7	Risk reporting capability
T9	Deeper data insight
T12	Rapid change in data volumes lead to a need for BI
T15	Expanding ERP, Enterprise Resource Planning
T16	Data availability readiness
T17	Forward-looking view': Forecasting
T22	Single version of truth
T23	Current and accurate information
T24	Rapidly change of information needs

The technological context can be an incentive to adopt BI; it also can become an obstacle to the BI adoption. The major obstacle that faced in BI implementation is the maturity of BI technologies in Malaysia. Hence, the readiness of the backbone infrastructure, data warehouse and implementation were the distinction to adopt BI. The eight barriers statements to spell the technological obstacles in implementing BI were formulated.

Table 8: List of Technological Barriers to BI Adoption

Code	Description
BT4	Lack of skills to implement BI / Data Warehouse
BT9	Lack of technology (pre-BI infrastructure)
BT10	Data security concerns (Pervasive BI and Outsourced version)
BT14	Frequent data latency issues
BT16	BI project complexity
BT18	BI tools highly specialized for wide spread use
BT19	Complexities of data management
BT20	Fragmented data sources in the enterprise

3.4.3.2 Organisational Drivers and Barriers to BI Adoption

Demands derived from organisations which involve profitability, operations, efficiency, marketing and customer needs have acted as the essential inspiration to drive the BI adoption in a business. Profits increment by enlarging the customer market share or costs decrement by improving the operations efficiency are the common objectives to be achieved. Herewith the fourteen (14) driver statements with the coverage of overall aspects of organisational drivers were formulated. These statements have been incorporated into questionnaire by aiming to gather the view from respondents which representing the business trends.

Table 9: List of Organisation Drivers to BI Adoption

Code	Description
O1	Reduce information analysis cost
O3	Increase profitability
O6	Risk mitigation (Financial or Operational)
O8	Optimization in resource allocation
O10	Organisational efficiency (Financial or Operational)
O13	Governance requirements (IT & Corporate)
O18	Align with corporate strategy
O19	Effective decision making at all levels of company
O20	Predict market trends
O21	Improve enterprise performance
O25	Customer service excellence
O26	More efficient service
O27	Increase service costs
O28	Better and faster decisions

However, the organisational context sometimes is a show stopper to the BI implementation especially when involved a huge investment. Basically there is a common conflict in the business where organisation intends to increase profit by adopting advance technology application but the high implementation costing without the justified return of investment has giving a hard time. Therefore, nine (9) common barriers encountered in the organisation had been listed to measure the significant relationship against the BI adoption throughout a survey.

Table 10: List of Organisation Barriers to BI Adoption

Code	Description
BO1	Upfront costs
BO2	Setup costs
BO3	Running costs
BO5	Lack of executive board interest
BO6	No real or tangible benefits
BO7	Poor Return of Investment (ROI)
BO8	Lack of knowledge about BI products
BO15	Implementation time lags
BO17	High costs of OLAP based systems (BI tuned)

3.4.3.3 Environmental Drivers and Barriers to BI Adoption

Besides the internal forces, the business environment factors also contribute some pressures to a corporate in the decision of BI adoption. The majority motivation is come from business competition, stakeholders or BI vendor which are play an important role in business. Based on study conducted, three (3) environmental drivers have been derived to assess the significant correlated level between these drivers with BI adoption.

Table 11: List of Environment Drivers to BI Adoption

Code	Description
E2	Increase business competitiveness
E11	Vendor website role in BI buying decision
E14	Stakeholder demands

In other hand, insufficient supports from external parties or underlined technologies might lead to the failure of implement BI system in a corporate. There were three (3) environment barriers formulated to spell the obstacles facing when a corporate intends to implement BI system.

Table 12: List of Environment Barriers to BI Adoption

Code	Description
BE11	Insufficient government support for BI initiatives
BE12	Lack of a complete BI Suite offering by any vendor
BE13	Typical BI systems not optimized for OLTP

3.5 Statistical Testing

In this research project, a few selected statistical testing were conducted against the data collected. First of all, the reliability analysis for BI drivers and barriers were conducted by evaluating the Cronbach's alpha. Secondly, the descriptive analysis was carried out to describe the demographic of respondents. The mean and standard deviation for BI drivers and barriers were derived to determine the ranking. The testing was continued with regression and one-way ANOVA analysis to discover the relationship between drivers/barriers and BI modules adoption.

3.5.1 Reliability Analysis

Reliability analysis allows the researcher to study the consistency and stability measurement of the items (Reliability Analysis, 2011). Cronbach's alpha is a model of internal consistency based on the average inter-item correlation (Sekaran & Bougie, 2010). The internal consistency reliability is higher when the Cronbach's alpha is closer to one (1). In general, the items with Cronbach's alpha less than 0.60 is considered poor where around 0.70 is acceptable and 0.80 is good.

In order the study the consistency of BI drivers and barriers, there were two (2) separate reliability tests conducted to retrieve the Cronbach's alpha value. The drivers are in the good range with the Cronbach's alpha of 0.659 which is above 0.60 where barriers are scored badly with Cronbach's alpha of 0.386.

Table 13: Reliability Statistical Result for BI Drivers and Barriers

Scale	**N of Items**	**Cronbach's Alpha**
BI Drivers	28	.659
BI Barriers	20	.386

Since the barriers scored badly, an extended analysis was conducted to improve the Cronbach's alpha. The decision to remove some of the items was made by referring to Table 14 which has consists the Cronbach's alpha value if the item has deleted.

Table 14: Statistical for Barrier Items

Items of Barrier	Cronbach's Alpha if Item Deleted
BO1: Upfront costs	.380
BO2: Setup costs	.349
BO3: Running costs	.359
BT4: Lack of skills to implement BI / Data Warehouse	.383
BO5: Lack of executive board interest	.387
BO6: No real or tangible benefits	.359
BO7: Poor Return of Investment (ROI)	.377
BO8: Lack of knowledge about BI products	.333
BT9: Lack of technology (pre-BI infrastructure)	.386
BT10: Data security concerns (Pervasive BI and Outsourced version)	.370
BE11: Insufficient government support for BI initiatives	.421
BE12: Lack of a complete BI Suite offering by any vendor	.375
BE13: Typical BI systems not optimized for OLTP	.352
BT14: Frequent data latency issues	.393
BO15: Implementation time lags	.311
BT16: BI project complexity	.372
BO17: High costs of OLAP based systems (BI tuned)	.374
BT18: BI tools highly specialized for wide spread use	.398
BT19: Complexities of data management	.416
BT20: Fragmented data sources in the enterprise	.377

By removing two barriers of BE11 (Insufficient government support for BI initiatives) and BT19 (Complexities of data management) from reliability analysis, the Cronbach's alpha for barriers has increased to 0.453. Although the value is far behind 0.60 but it has improved 0.067 after removed these two barriers.

Table 15: Reliability Statistical Result for BI Drivers and Barriers after Deletion

Scale	N of Items	Cronbach's Alpha
BI Drivers	28	.659
BI Barriers (after deletion of 2 items)	18	.453

3.5.2 Descriptive Analysis

A descriptive analysis was conducted to describe the demographic of respondents. The descriptions inclusive of the basic demographic information such as gender, age, position, user type for BI, company industry and IT annual budget. The descriptive analysis was extended to analyse the BI adoption level and IT-Business initiatives.

3.5.3 Mean & Standard Deviation

The mean and standard deviation scoring for twenty eight (28) drivers and twenty (20) barriers were computed to determine the ranking. The top three highest and lowest mean score of drivers and barriers were defined to be further compared with regression and one-way ANOVA analysis result.

3.5.4 Regression Analysis

The overall relationships of drivers/barriers with each BI module adoption were analysed by using the regression analysis. The analyses were extended to regression stepwise procedure to select the significant drivers/barriers to BI adoption in Malaysia.

3.5.5 One-way ANOVA Analysis

The further testing was conducted to ensure the significant relationship between individual driver/barrier with BI module adoption which discovered in stepwise regression analysis. One-way ANOVA always is the best choice to test one-to-one relationship.

CHAPTER 4

DATA ANALYSIS AND RESEARCH RESULT

4.1 Introduction

This chapter presents the results of analysis conducted by using various techniques to describe the data behaviour accurately. The first section includes the descriptive statistics of BI adoption level, IT-Business initiatives, mean and standard deviation scoring for BI drivers and barriers. The second section describes the regression analysis results for enter and stepwise method. The last section explains the one-way ANOVA results for one-to-one relationship.

4.2 Descriptive Analysis

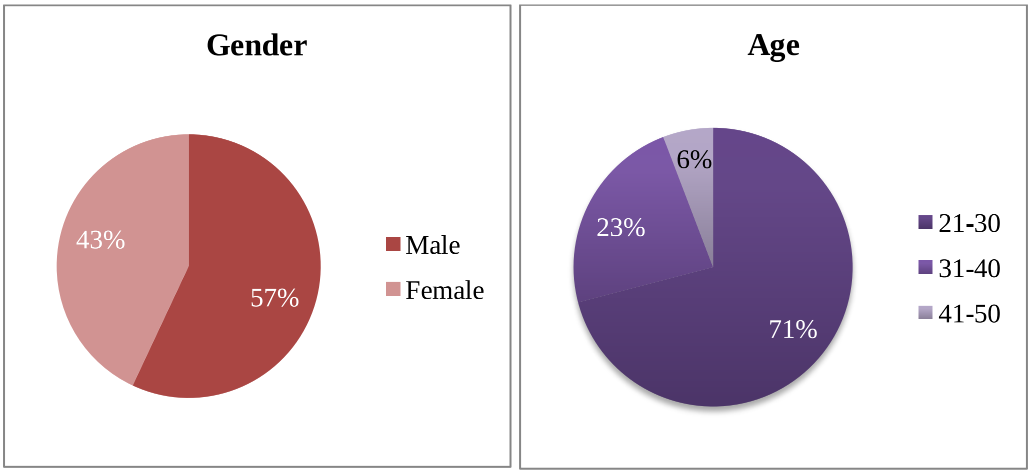
The descriptive analysis for respondents' demographic was conducted to study the data behaviour in general. Subsequently, the BI adoption level and IT-Business initiatives were studied to spell the status of respondents. In additional, the mean and standard deviation scoring for twenty eight drivers and twenty barriers were derived to identify the highest selection by respondents.

4.2.1 Demographic Profile

The basic demographic profiles such as age, gender, position, user type for BI, company industry and annual IT budget were collected through the survey which represents the various backgrounds of respondents. A total of sixty eight (86) respondents were received with completed answers to be participant in this unit analysis. The unit of analysis was the individual respondents which responded to the survey.

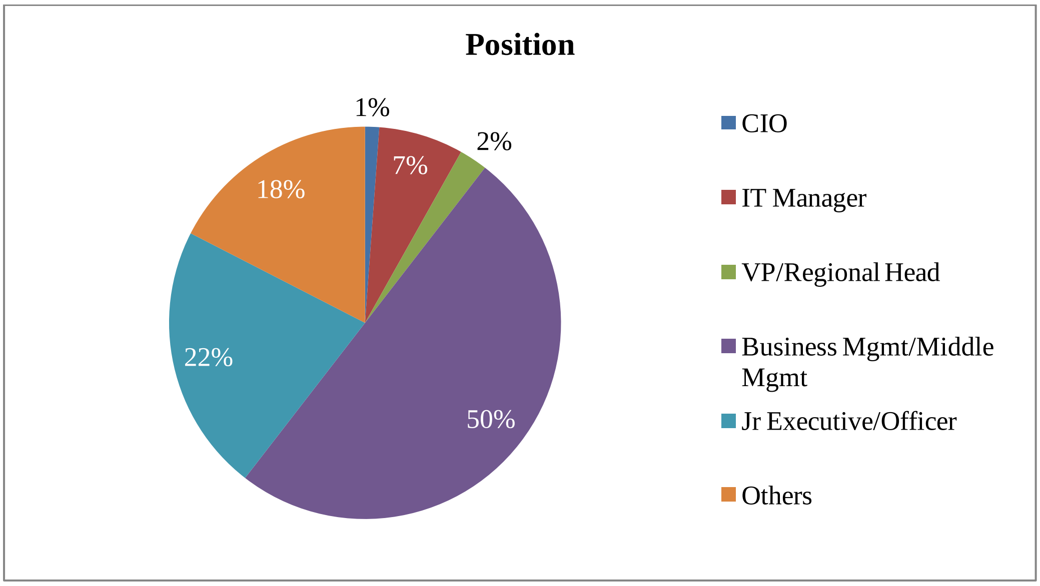
The pie charts represent the unit of analysis are shown in Figure 7. The sampling comprised of 57.0% (49 persons) male and 43.0% (37 persons) female where majority respondents were in the range of twenty one (21) to thirty (30) which consisted 70.9% (61 persons). There were 23.3% (20 persons) falls into age group of thirty one (31) to forty (40) and 5.8% (5 persons) in age group of forty one (41) to fifty (50).

Figure 7: Pie Charts for Respondents' Gender and Age



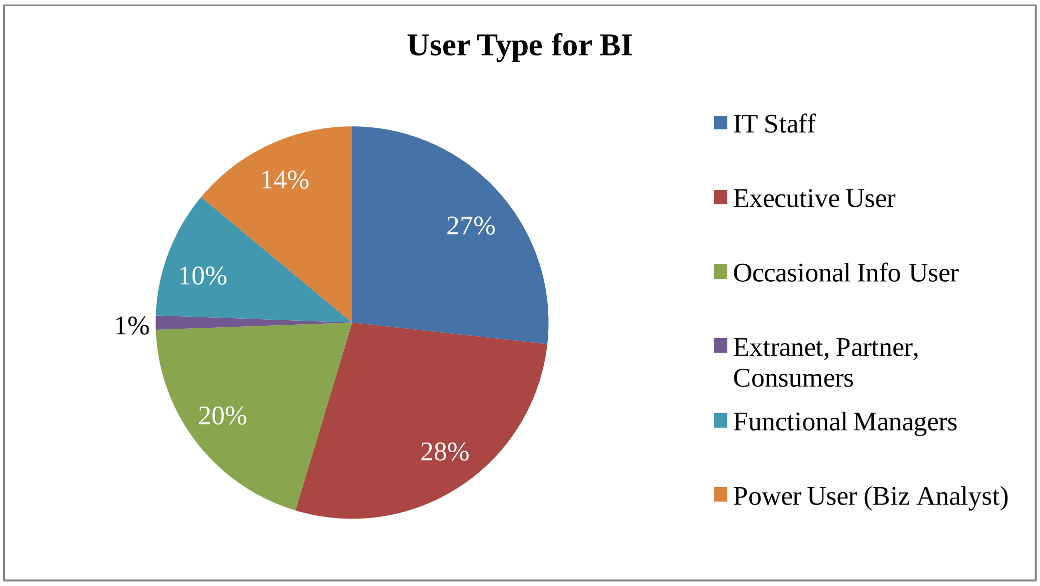
As shown in Figure 8, the respondents who work at the position of business management or middle management in an organisation comprised 50% (43 persons) and follows with junior executive or officer has 22.1% (19 persons). Subsequently the other positions which were not listed had comprising 17.4% (15 persons). The position of IT manager, VP or regional head and CIO were containing 7.0% (6 persons), 2.3% (2 persons) and 1.2% (1 person) respectively.

Figure 8: Pie Chart for Respondents' Position



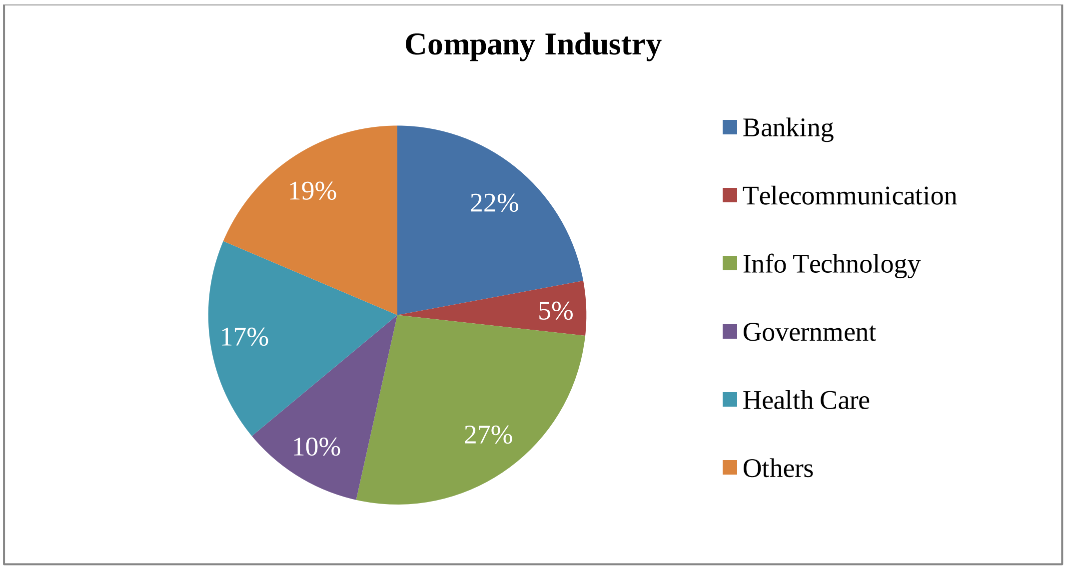
Throughout respondents collected as shown in Figure 9, majority of user type for BI was executive user and IT staff which had consisting 27.9% (24 persons) and 26.7% (23 persons) respectively. Follows by the occasional information user and power users of business analyst were comprising 19.8% (17 persons) and 14.0% (12 persons). Lastly only a BI user as extranet, partner or consumer was participant in this research which had comprising 1.2% (1 person).

Figure 9: Pie Chart for Respondents' User Type for BI



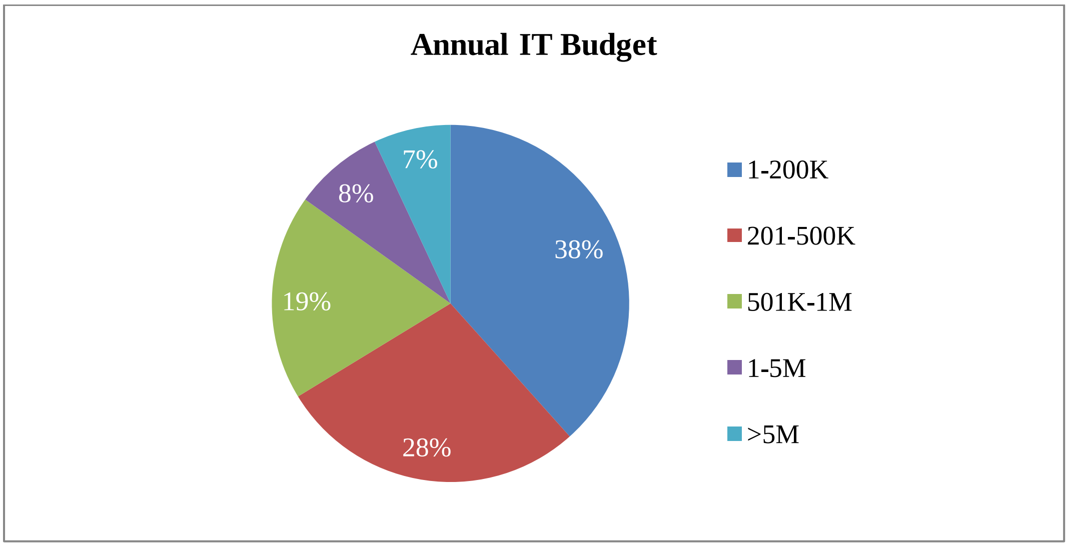
There were 26.7% (23 persons) respondents worked in information technology industry where 22.1% (19 persons) employed in banking industry as shown in Figure 10. 18.6% (16 persons) respondents were serviced in other industries which were not listed where 17.4% (15 persons) worked in health care industry. The balance respondents were employed in government and telecommunication industry with the rate of 10.5% (9 persons) and 4.7% (4 persons) from the total.

<u>Figure 10: Pie Chart for Company Industry</u>



An annual IT budget represents the necessity of IT adoption in an organisation. 38.4% (33) of the organisations that respondents worked at spent up to Malaysia Ringgit of two hundred thousand (RM 200,000) annually for IT as shown in Figure 11. Follows by 27.9% (24) allocated below Malaysia Ringgit of five hundred thousand (RM 500,000) for annual IT budget. There were 18.6% (16) organisations spent up to Malaysia Ringgit one million (RM 1 million) where 8.1% (7) allocated up to Malaysia Ringgit five million (RM 5 million) for annual IT budget. Only 7.0% (6) organisations were willing to spend more than Malaysia Ringgit five million (RM5 million) annually on IT budget.

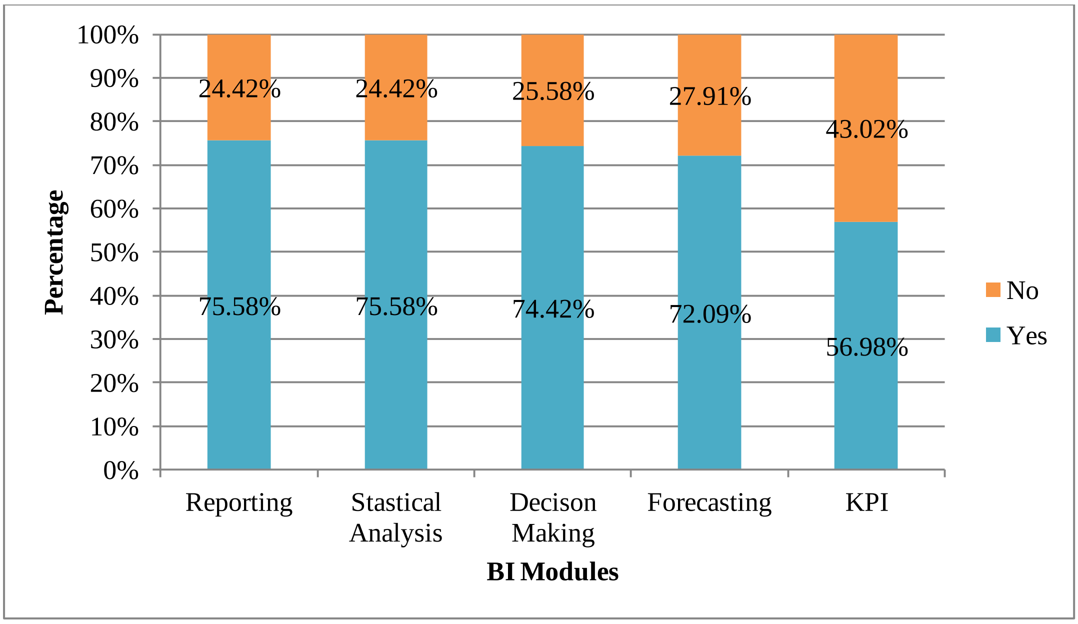
Figure 11: Pie Chart for Company Annual IT Budget



4.2.2 BI Adoption Level in Malaysia

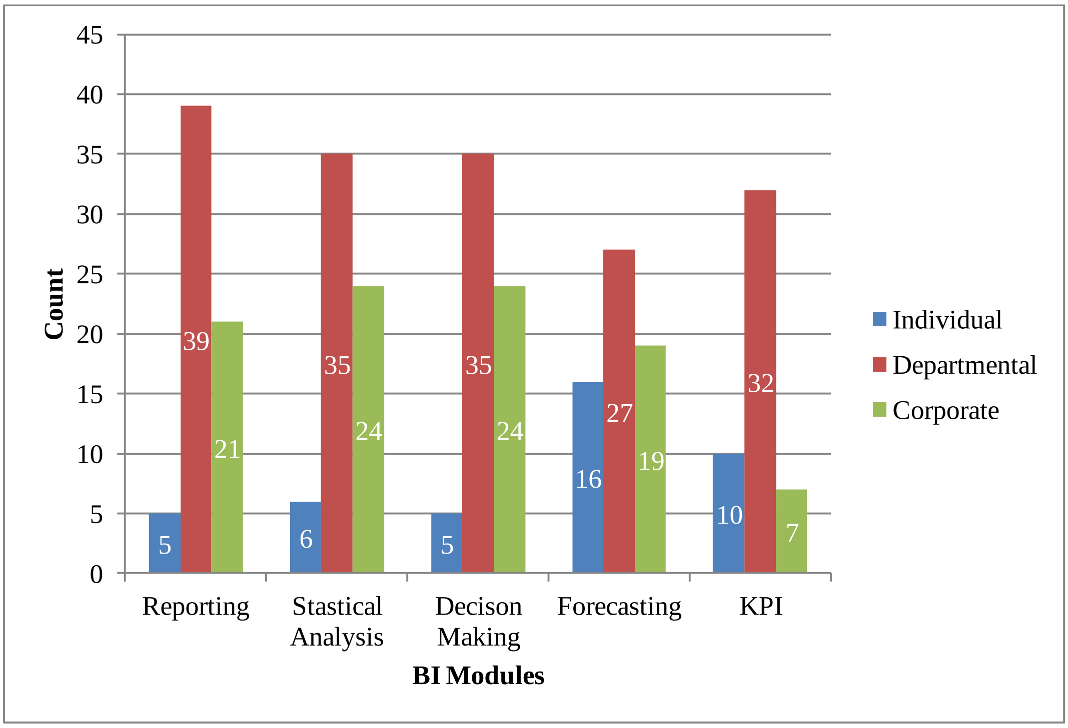
The BI adoption level among the sixty eight (86) respondents collected was respectively high as shown in Figure 12. Overall, there were greater than 70% (60 persons) respondents adopted BI reporting, statistical, decision making and forecasting where only 56.98% (49 persons) respondents were adopting BI KPI.

Figure 12: Bar Chart for BI Modules Adoption in Malaysia



An extended analysis against the BI adoption was carried out to examine the adoption level for each BI module as displayed in Figure 13. In overall, the major corporate are implementing BI at departmental level which consists at least 40% from the respondents. The second highest BI adoption level is corporate level compare to individual except for BI KPI. This result represents the BI has been started using at department and corporate level in Malaysia to fully utilise the benefits across all levels of the corporate.

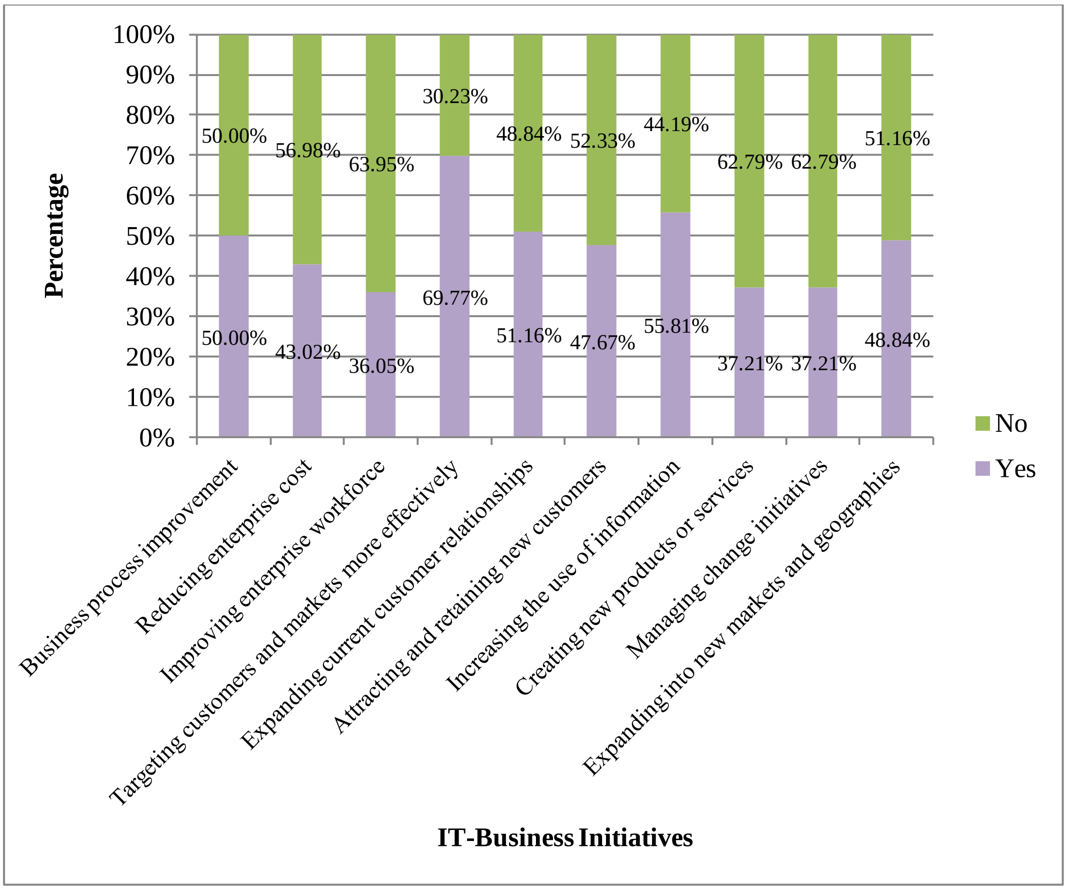
Figure 13: Bar Chart for BI Adoption Level by Modules in Malaysia



4.2.3 IT-Business Initiatives

In corporate, IT strategy needs to be in aligned with business directions to gain the competitive advantage. Therefore, IT-Business initiatives in a corporate are essential in order to implementing BI. Among the ten initiatives scoring as shown in Figure 14, the top three highest scores are ‘Target customer and markets more effectively’, ‘Increasing the use of information’ and ‘Expanding current customer relationships’ which scored 69.77% (60 respondents), 55.81% (48 respondents) and 51.16% (44 respondents) respectively. The good response on these initiatives is leading the corporate to implement more IT application inclusive of BI.

Figure 14: Bar Chart for IT-Business Initiatives



4.2.4 Mean and Standard Deviation Scoring for BI Drivers

The mean and standard deviation for twenty eight (28) BI drivers was carried out as shown in Table 16 to determine the significant drivers by comparing the mean score. The highest mean score represents the significant driver where the lowest mean score represents the non-significant driver.

Based on sixty eight (68) respondents, T12 (Rapid change in data volumes lead to a need for BI) and T9 (Deeper data insight) are scored highest in mean and the scores are closed to each other (3.57 and 3.56 out of 5.00). The third highest mean score is E2 (Increase business competitiveness) which has 3.50.

The three top lowest mean scores which less agreed by respondents are T22 (Single version of truth), O13 (Government requirement (IT & Corporate) and E14 (Stakeholder demands). Their mean scoring are from range of 2.69 to 2.72 which is less than neutral score.

Table 16: Mean and Standard Deviation Scoring for BI Drivers

BI Drivers	Mean	Std. Deviation
T12:Rapid change in data volumes lead to a need for BI	3.57	1.242
T9:Deeper data insight	3.56	1.223
E2:Increase business competitiveness	3.50	1.378
O20:Predict market trends	3.49	1.215
O25:Customer service excellence	3.47	.929
T23:Current and accurate information	3.37	1.179
O19:Effective decision making at all levels of company	3.36	1.264
O28:Better and faster decisions	3.35	1.253
O21:Improve enterprise performance	3.33	1.297
T24:Rapidly change of information needs	3.31	1.258
O18:Align with corporate strategy	3.22	.832
T5:Availability of data analysis tool	3.21	1.321
O6:Risk mitigation (Financial or Operational)	3.20	1.136
O8:Optimizaton in resource allocation	3.20	1.263
O1:Reduce information analysis cost	3.19	1.143
E11:Vendor website role in BI buying decision	3.19	.790
O3:Increase profitability	3.19	1.393
T4:Enterprise wide data driven decision making capability	3.16	1.327
O10:Organisational efficiency (Financial or Operational)	3.15	1.288
O27:Increase service costs	3.02	.735
O26:More efficient service	3.02	1.127
T17:Forward-looking view': Forecasting	2.95	1.245
T7:Risk reporting capability	2.86	1.118
T16:Data availability readiness	2.81	1.068
T15:Expanding ERP, Enterprise Resource Planning	2.76	1.274
T22:Single version of truth	2.72	.916

O13:Governance requirements (IT & Corporate)	2.71	.944
E14:Stakeholder demands	2.69	.924

4.2.5 Mean and Standard Deviation Scoring for BI Barriers

The mean and standard deviation for twenty BI barriers was carried out as shown in Table 17 to identify the significant barriers by comparing the mean score. The highest mean score represents the significant barrier where the lowest mean score represents the non-significant barrier.

Based on sixty eight respondents, the barriers of costing are scoring the top three highest mean which are BO2 (Setup costs), BO1 (Upfront costs) and BO3 (Running costs). Their mean scores are 3.88, 3.77 and 3.67 respectively. This represents the costing still a major barrier in majority in order to implementing BI..

The three top lowest mean scores which less agreed by respondents are BO17 (High costs of OLAP based systems (BI tuned)), BT19 (Complexities of data management) and BO7 (Poor Return of Investment (ROI)). Their mean scoring are from range of 2.94 to 3.08 which is close to neutral score.

Table 17: Mean and Standard Deviation Scoring for BI Barriers

BI Barriers	Mean	Std. Deviation
BO2: Setup costs	3.88	.860
BO1: Upfront costs	3.77	.966
BO3: Running costs	3.67	.860
BT4: Lack of skills to implement BI / Data Warehouse	3.64	.893
BE12: Lack of a complete BI Suite offering by any vendor	3.47	.979
BT14: Frequent data latency issues	3.47	.979
BO5: Lack of executive board interest	3.42	1.122
BE11: Insufficient government support for BI initiatives	3.41	1.231
BE13: Typical BI systems not optimized for OLTP	3.35	.878
BT16: BI project complexity	3.30	1.159
BO6: No real or tangible benefits	3.29	1.235
BT10: Data security concerns (Pervasive BI and Outsourced version)	3.24	1.040
BO15: Implementation time lags	3.21	1.030
BT9: Lack of technology (pre-BI infrastructure)	3.14	1.097
BT18: BI tools highly specialized for wide spread use	3.13	.905
BO8: Lack of knowledge about BI products	3.12	1.121
BT20: Fragmented data sources in the enterprise	3.10	1.148
BO17: High costs of OLAP based systems (BI tuned)	3.08	1.065
BT19: Complexities of data management	3.01	1.122
BO7: Poor Return of Investment (ROI)	2.94	1.231

4.3 Regression Analysis for BI Drivers

Regression analysis was performed to analyse the relationship between twenty eight drivers and BI adoptions. The objective of this analysis is to use the twenty eight drivers as independent variables to predict each individual BI adoption as the single dependent value. Extended analysis of stepwise estimation procedure also was conducted to maximise the incremental explained variance at each step of model building. The highest bivariate correlation with the BI each individual adoption will be selected.

4.3.1 Regression Analysis on BI drivers against Reporting Adoption

First of all, a regression analysis on twenty eight drivers against BI reporting adoption was carried out. Based on analysis result in Table 18, the P-value in ANOVA is 0.081 which is more than 0.05. Therefore, there is no significant relationship between twenty eight drivers and BI reporting adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There is 43.2% of total of Y (BI reporting adoption) explained by the regression model consisting of twenty eight drivers.

Table 18: Summary of Regression Analysis between twenty eight drivers with BI Reporting Adoption

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.657[a]	.432	.153	.398	.432	1.548	28	57	.081

Dependent Variable: Adopt Reporting

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.856	28	.245	1.548	.081[a]
	Residual	9.016	57	.158		
	Total	15.872	85			

Dependent Variable: Adopt Reporting

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.743	.550		1.352	.182
	O1:Reduce information analysis cost	-.053	.048	-.140	-1.093	.279
	E2:Increase business competitiveness	.059	.039	.188	1.530	.131
	O3:Increase profitability	.020	.039	.064	.506	.615
	T4:Enterprise wide data driven decision making capability	-.028	.041	-.085	-.667	.508
	T5:Availability of data analysis tool	.025	.041	.078	.622	.536
	O6:Risk mitigation (Financial or Operational)	.032	.047	.084	.687	.495
	T7:Risk reporting capability	-.045	.047	-.118	-.965	.339
	O8:Optimizaton in resource allocation	-.095	.048	-.279	-1.989	.052
	T9:Deeper data insight	-.005	.041	-.014	-.117	.907
	O10:Organisational efficiency (Financial or Operational)	-.017	.044	-.051	-.390	.698

E11:Vendor website role in BI buying decision	-.014	.064	-.026	-.224	.824
T12:Rapid change in data volumes lead to a need for BI	-.073	.047	-.210	-1.545	.128
O13:Governance requirements (IT & Corporate)	.045	.054	.097	.831	.410
E14:Stakeholder demands	-.053	.058	-.113	-.911	.366
T15:Expanding ERP, Enterprise Resource Planning	-.013	.045	-.039	-.296	.768
T16:Data availability readiness	.008	.047	.020	.173	.863
T17:Forward-looking view': Forecasting	.007	.041	.020	.166	.869
O18:Align with corporate strategy	.065	.064	.125	1.009	.317
O19:Effective decision making at all levels of company	-.064	.044	-.186	-1.451	.152
O20:Predict market trends	.064	.048	.179	1.333	.188
O21:Improve enterprise performance	-.041	.044	-.122	-.918	.363
T22:Single version of truth	.037	.060	.079	.627	.533
T23:Current and accurate information	-.029	.049	-.079	-.586	.560
T24:Rapidly change of information needs	.044	.044	.129	1.010	.317
O25:Customer service excellence	.036	.058	.078	.624	.535
O26:More efficient service	.015	.046	.038	.321	.749
O27:Increase service costs	-.097	.071	-.165	-1.368	.177
O28:Better and faster decisions	.159	.046	.460	3.482	.001

Dependent Variable: Adopt Reporting

4.3.1.1 Stepwise Regression on BI drivers against Reporting Adoption

The regression analysis then extended to stepwise estimation procedure to select the driver/s that has highest bivariate correlation with BI reporting adoption. The first step is to build a regression equation just using a single independent (O28, Better and faster decisions) as identified above. As shown in Table 19, the P-value in ANOVA is 0.000 which is less than 0.05, therefore there is a significant relationship between O28 and BI reporting adoption.

Table 19: Stepwise Regression Analysis Result for BI Reporting Adoption

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.441[a]	.195	.185	.390	.195	20.337	1	84	.000

a. Predictors: (Constant), O28:Better and faster decisions

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.094	1	3.094	20.337	.000[a]
	Residual	12.778	84	.152		
	Total	15.872	85			

a. Predictors: (Constant), O28:Better and faster decisions

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.246	.121		2.040	.044
	O28:Better and faster decisions	.152	.034	.441	4.510	.000

a. Dependent Variable: Adopt Reporting

4.3.2 Regression Analysis on BI drivers against Statistical Adoption

Regression analysis on twenty eight drivers against BI statistical adoption was performed. As shown in Table 20, the P-value in ANOVA is 0.524 which is more than 0.05. Therefore, there is no significant relationship between twenty eight drivers and BI statistical adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There is 32.2% of total of Y (BI statistical adoption) explained by the regression model consisting of twenty eight drivers.

Table 20: Regression Analysis Result between twenty eight drivers with BI Statistical Adoption

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.568[a]	.322	-.010	.434	.322	.969	28	57	.524

Dependent Variable: Adopt Statistical

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.118	28	.183	.969	.524[a]
	Residual	10.754	57	.189		
	Total	15.872	85			

Dependent Variable: Adopt Statistical

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.027	.600		1.711	.093
	O1:Reduce information analysis cost	-.004	.053	-.010	-.072	.943
	E2:Increase business competitiveness	.048	.042	.153	1.139	.259
	O3:Increase profitability	.003	.043	.011	.081	.935
	T4:Enterprise wide data driven decision making capability	.030	.045	.092	.668	.507
	T5:Availability of data analysis tool	-.030	.045	-.091	-.668	.507
	O6:Risk mitigation (Financial or Operational)	-.037	.051	-.097	-.721	.474
	T7:Risk reporting capability	.045	.051	.116	.872	.387
	O8:Optimizaton in resource allocation	.016	.052	.047	.309	.758
	T9:Deeper data insight	-.049	.045	-.138	-1.084	.283
	O10:Organisational efficiency (Financial or Operational)	-.036	.048	-.108	-.748	.458
	E11:Vendor website role in BI buying decision	-.054	.069	-.099	-.778	.440
	T12:Rapid change in data volumes lead to a need for BI	-.070	.052	-.201	-1.358	.180
	O13:Governance requirements (IT & Corporate)	-.045	.059	-.099	-.772	.443
	E14:Stakeholder demands	.072	.063	.153	1.132	.262
	T15:Expanding ERP, Enterprise Resource Planning	-.049	.049	-.145	-1.006	.319
	T16:Data availability readiness	-.018	.051	-.044	-.346	.731
	T17:Forward-looking view': Forecasting	-.008	.045	-.024	-.187	.852
	O18:Align with corporate strategy	.048	.070	.092	.678	.500

O19:Effective decision making at all levels of company	.063	.048	.184	1.313	.194
O20:Predict market trends	.080	.052	.225	1.537	.130
O21:Improve enterprise performance	.025	.048	.074	.510	.612
T22:Single version of truth	-.064	.065	-.136	-.987	.328
T23:Current and accurate information	.007	.054	.019	.127	.900
T24:Rapidly change of information needs	-.019	.048	-.054	-.388	.699
O25:Customer service excellence	.003	.063	.006	.042	.966
O26:More efficient service	-.011	.050	-.029	-.227	.822
O27:Increase service costs	-.053	.078	-.091	-.689	.494
O28:Better and faster decisions	.007	.050	.020	.136	.892

Dependent Variable: Adopt Statistical

4.3.2.1 Stepwise Regression on BI drivers against Statistical Adoption

The regression analysis then extended to stepwise estimation procedure to select the driver/s that has highest bivariate correlation with BI statistical adoption. The first step is to build a regression equation just using a single independent (O20, Predict market trends) as identified above. The P-value in ANOVA is 0.011 as shown in Table 21 which is less than 0.05, therefore there is a significant relationship between O20 and BI statistical adoption.

Table 21: Stepwise Regression Analysis Result for BI Statistical Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.275[a]	.075	.064	.418	.075	6.851	1	84	.011

a. Predictors: (Constant), O20:Predict market trends

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.197	1	1.197	6.851	.011[a]
	Residual	14.675	84	.175		
	Total	15.872	85			

a. Predictors: (Constant), O20:Predict market trends

b. Dependent Variable: Adopt Statistical

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.415	.138		3.014	.003
	O20:Predict market trends	.098	.037	.275	2.618	.011

a. Dependent Variable: Adopt Statistica

4.3.3 Regression Analysis on BI drivers against Decision Making Adoption

Regression analysis on twenty eight drivers against BI decision making adoption was performed. The overall P-value is 0.109 as shown in Table 22 which is more than 0.05. Therefore, there is no significant relationship between twenty eight drivers and BI decision making adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There is 41.9% of total of Y (BI decision making adoption) explained by the regression model consisting of twenty eight drivers.

Table 22: Regression Analysis Result between twenty eight drivers with BI Decision Making Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.648[a]	.419	.134	.408	.419	1.470	28	57	.109

Dependent Variable: Adopt Decision Making

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.865	28	.245	1.470	.109[a]
	Residual	9.507	57	.167		
	Total	16.372	85			

Dependent Variable: Adopt Decision Making

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.785	.565		1.391	.170
	O1:Reduce information analysis cost	-.045	.050	-.116	-.899	.373
	E2:Increase business competitiveness	-.046	.040	-.144	-1.160	.251
	O3:Increase profitability	.006	.040	.018	.142	.887
	T4:Enterprise wide data driven decision making capability	.023	.042	.070	.549	.585
	T5:Availability of data analysis tool	-.060	.042	-.181	-1.434	.157
	O6:Risk mitigation (Financial or Operational)	.008	.048	.021	.166	.869
	T7:Risk reporting capability	.024	.048	.062	.503	.617
	O8:Optimizaton in resource allocation	.166	.049	.478	3.373	.001
	T9:Deeper data insight	-.026	.042	-.071	-.605	.547
	O10:Organisational efficiency (Financial or Operational)	-.075	.045	-.219	-1.638	.107
	E11:Vendor website role in BI buying decision	.025	.065	.045	.380	.705
	T12:Rapid change in data volumes lead to a need for BI	.082	.048	.232	1.693	.096
	O13:Governance requirements (IT & Corporate)	-.033	.055	-.072	-.608	.545
	E14:Stakeholder demands	-.048	.060	-.101	-.804	.425
	T15:Expanding ERP, Enterprise Resource Planning	.113	.046	.329	2.474	.016
	T16:Data availability readiness	-.007	.048	-.017	-.141	.888
	T17:Forward-looking view': Forecasting	.026	.042	.075	.621	.537
	O18:Align with corporate strategy	.011	.066	.021	.168	.867
	O19:Effective decision making at all levels of company	-.093	.045	-.267	-2.059	.044
	O20:Predict market trends	-.032	.049	-.089	-.654	.516
	O21:Improve enterprise performance	-.053	.045	-.157	-1.171	.247
	T22:Single version of truth	.084	.061	.176	1.377	.174
	T23:Current and accurate information	.089	.051	.240	1.762	.084
	T24:Rapidly change of information needs	-.064	.045	-.185	-1.429	.158
	O25:Customer service excellence	.000	.060	-.001	-.011	.991
	O26:More efficient service	-.055	.047	-.141	-1.166	.248
	O27:Increase service costs	.015	.073	.025	.208	.836
	O28:Better and faster decisions	-.027	.047	-.078	-.584	.561

Dependent Variable: Adopt Decision Making

4.3.3.1 Stepwise Regression on BI drivers against Decision Making Adoption

The regression analysis then extended to stepwise estimation procedure to select the driver/s that has highest bivariate correlation with BI decision making adoption. The first step is to build a regression equation just using a single independent (O28, Better and faster decisions) which has the highest bivariate correlation. The P-value in ANOVA is 0.014 which is less than 0.05, therefore there is a significant relationship between O28 and BI decision making adoption.

In second step, the regression stepwise estimation procedure successfully identified a second independent variable (T22, Single version of truth) among the exclusion variables in first step which has highest bivariate correlation. By adding both independent variables (O28 and T22) into regression equation, the P-value in ANOVA is 0.007 which is less than 0.05. Hence, O28 and T22 are significant related to BI decision making adoption.

In third step, the regression stepwise estimation procedure successfully discovered a third independent variable (O19, Effective decision making at all levels of company) among the exclusion variables in second step which has highest bivariate correlation. By adding all three independent variables (O28, T22 and O19) into regression equation, the P-value in ANOVA is 0.002 as shown in Table 23 which is less than 0.05. Hence, O28, T22 and O19 are significant related to BI decision making adoption.

<u>Table 23: Stepwise Regression Analysis Result for BI Decision Making Adoption</u>

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.264[a]	.069	.058	.426	.069	6.273	1	84	.014
2	.337[b]	.114	.092	.418	.044	4.155	1	83	.045
3	.404[c]	.163	.132	.409	.049	4.810	1	82	.031

a. Predictors: (Constant), O28:Better and faster decisions

b. Predictors: (Constant), O28:Better and faster decisions, T22:Single version of truth

c. Predictors: (Constant), O28:Better and faster decisions, T22:Single version of truth, O19:Effective decision making at all levels of company

ANOVA[d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.138	1	1.138	6.273	.014[a]
	Residual	15.234	84	.181		
	Total	16.372	85			
2	Regression	1.864	2	.932	5.332	.007[b]
	Residual	14.508	83	.175		
	Total	16.372	85			
3	Regression	2.668	3	.889	5.321	.002[c]
	Residual	13.704	82	.167		
	Total	16.372	85			

a. Predictors: (Constant), O28:Better and faster decisions

b. Predictors: (Constant), O28:Better and faster decisions, T22:Single version of truth

c. Predictors: (Constant), O28:Better and faster decisions, T22:Single version of truth, O19:Effective decision making at all levels of company

d. Dependent Variable: Adopt Decision Making

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.053	.132		7.999	.000
	O28:Better and faster decisions	-.092	.037	-.264	-2.505	.014
2	(Constant)	.722	.208		3.479	.001
	O28:Better and faster decisions	-.077	.037	-.220	-2.089	.040
	T22:Single version of truth	.103	.051	.215	2.038	.045
3	(Constant)	.920	.222		4.143	.000
	O28:Better and faster decisions	-.066	.036	-.188	-1.803	.075
	T22:Single version of truth	.112	.050	.234	2.264	.026
	O19:Effective decision making at all levels of company	-.078	.035	-.224	-2.193	.031

a. Dependent Variable: Adopt Decision Making

4.3.4 Regression Analysis on BI drivers against Forecasting Adoption

Regression analysis on twenty eight drivers against BI forecasting adoption was performed. As shown in Table 24, the overall P-value is 0.077 which is more than 0.05. Therefore, there is no significant relationship between twenty eight drivers and BI forecasting adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There is 43.4% of total of Y (BI forecasting adoption) explained by the regression model consisting of twenty eight drivers.

Table 24: Regression Analysis Result between twenty eight drivers with BI Forecasting Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.659[a]	.434	.156	.415	.434	1.561	28	57	.077

Dependent Variable: Adopt Forecasting

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.508	28	.268	1.561	.077[a]
	Residual	9.794	57	.172		
	Total	17.302	85			

Dependent Variable: Adopt Forecasting

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.643	.573		1.122	.266
	O1:Reduce information analysis cost	-.056	.050	-.143	-1.122	.267
	E2:Increase business competitiveness	.006	.040	.017	.139	.890
	O3:Increase profitability	-.002	.041	-.006	-.050	.960
	T4:Enterprise wide data driven decision making capability	.068	.043	.201	1.585	.119
	T5:Availability of data analysis tool	.057	.043	.166	1.331	.189
	O6:Risk mitigation (Financial or Operational)	-.003	.049	-.007	-.058	.954
	T7:Risk reporting capability	-.020	.049	-.050	-.407	.685
	O8:Optimizaton in resource allocation	-.022	.050	-.061	-.435	.665
	T9:Deeper data insight	-.013	.043	-.036	-.309	.759
	O10:Organisational efficiency (Financial or Operational)	-.004	.046	-.010	-.077	.939
	E11:Vendor website role in BI buying decision	-.010	.066	-.017	-.144	.886
	T12:Rapid change in data volumes lead to a need for BI	-.027	.049	-.075	-.555	.581
	O13:Governance requirements (IT & Corporate)	.105	.056	.219	1.877	.066
	E14:Stakeholder demands	-.164	.060	-.335	-2.709	.009
	T15:Expanding ERP, Enterprise Resource Planning	.004	.047	.011	.084	.933

T16:Data availability readiness	.039	.049	.093	.802	.426
T17:Forward-looking view': Forecasting	-.076	.043	-.208	-1.758	.084
O18:Align with corporate strategy	-.014	.067	-.025	-.204	.839
O19:Effective decision making at all levels of company	-.048	.046	-.135	-1.052	.297
O20:Predict market trends	-.007	.050	-.018	-.134	.894
O21:Improve enterprise performance	-.006	.046	-.017	-.129	.898
T22:Single version of truth	.080	.062	.162	1.288	.203
T23:Current and accurate information	.042	.051	.109	.809	.422
T24:Rapidly change of information needs	-.040	.046	-.113	-.883	.381
O25:Customer service excellence	.137	.061	.283	2.265	.027
O26:More efficient service	-.038	.048	-.095	-.795	.430
O27:Increase service costs	-.077	.074	-.126	-1.046	.300
O28:Better and faster decisions	.097	.047	.269	2.037	.046

Dependent Variable: Adopt Forecasting

4.3.4.1 Stepwise Regression on BI drivers against Forecasting Adoption

The regression analysis then extended to stepwise estimation procedure to select the driver/s that has highest bivariate correlation with BI Forecasting adoption. The first step is to build a regression equation just using a single independent (O28, Better and faster decisions) which has the highest bivariate correlation. The P-value is 0.009 as shown in Table 25 which is less than 0.05, therefore there is a significant relationship between O28 and BI forecasting adoption. R square (R^2) is only 0.077 where has 7.7% of total of Y (BI forecasting adoption) explained by the regression model consisting O28.

In the second step, the regression stepwise estimation procedure successfully identified a second independent variable (E14: Stakeholder demands) among the exclusion variables in first step which has highest bivariate correlation. By adding both independent variables (O28 and E14) into regression equation, the P-value is 0.003 which is less than 0.05. Hence, O28 and E14 are significant related to BI forecasting adoption. R square (R^2) has increased to 13.1% of total of Y (BI forecasting adoption) explained by the regression model consisting O28 and E14.

In the third step, the regression stepwise estimation procedure successfully discovered a third independent variable (O25: Customer service excellence) among the exclusion variables in second step which has highest bivariate correlation. By adding all three independent variables (O28, E14 and O25) into regression equation, the P-value is 0.001 which is less than 0.05. Hence, O28, E14 and O25 are significant related to BI forecasting adoption. R square (R^2) has increased to 17.8% of total of Y (BI forecasting adoption) explained by the regression model consisting of three drivers.

In the forth step, the regression stepwise estimation procedure successfully discovered a forth independent variable (T4: Enterprise wide data driven decision making capability) among the exclusion variables in third step which has highest bivariate correlation. By adding all four independent variables (O28, E14, O25 and T4) into regression equation, the P-value is 0.000 which is less than 0.05. Hence, O28, E14, O25 and T4 are significantly related to BI forecasting adoption. R square (R^2) has increased to 21.7% of total of Y (BI forecasting adoption) explained by the regression model consisting O28, E14, O25 and T4.

Unfortunately, after T4 added into the stepwise regression equation, O28 (Better and faster decisions) is no longer significantly related to BI forecasting adoption where the O28 P-value is more than 0.05 (0.112). Therefore in the fifth step, the regression stepwise estimation procedure removed O28 from regression equation. Hence, the number of independent variables is reduced to three. After removing O28 from regression equation, the individual P-value for balance variables is maintained below 0.05 and overall P-value is 0.001 which is less than 0.05. Hence, E14, O25 and T4 are significantly related to BI decision making adoption. R square (R^2) has reduced to 19.2% of total of Y (BI forecasting adoption) explained by the regression model consisting E14, O25 and T4.

In the sixth step, the regression stepwise estimation procedure successfully discovered the next independent variable (O13: Governance requirements (IT & Corporate)) among the exclusion variables in fifth step which has highest bivariate correlation. By adding all four independent variables (E14, O25, T4 and O13) into regression equation, the P-value is 0.000 which is less than 0.05. Hence, E14, O25, T4 and O13 are significantly related to BI forecasting adoption. R square (R^2) has increased to 24.9% of total of Y (BI forecasting adoption) explained by the regression model consisting E14, O25, T4 and O13.

Table 25: Stepwise Regression Analysis Result for BI Forecasting Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.278[a]	.077	.066	.436	.077	7.046	1	84	.009
2	.361[b]	.131	.110	.426	.053	5.071	1	83	.027
3	.422[c]	.178	.148	.416	.048	4.767	1	82	.032
4	.466[d]	.217	.179	.409	.039	4.036	1	81	.048
5	.439[e]	.192	.163	.413	-.025	2.575	1	81	.112
6	.499[f]	.249	.212	.400	.057	6.141	1	81	.015

a. Predictors: (Constant), O28:Better and faster decisions

b. Predictors: (Constant), O28:Better and faster decisions, E14:Stakeholder demands

c. Predictors: (Constant), O28:Better and faster decisions, E14:Stakeholder demands, O25:Customer service excellence

d. Predictors: (Constant), O28:Better and faster decisions, E14:Stakeholder demands, O25:Customer service excellence, T4:Enterprise wide data driven decision making capability

e. Predictors: (Constant), E14:Stakeholder demands, O25:Customer service excellence, T4:Enterprise wide data driven decision making capability

f. Predictors: (Constant), E14:Stakeholder demands, O25:Customer service excellence, T4:Enterprise wide data driven decision making capability, O13:Governance requirements (IT & Corporate)

ANOVA[g]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.339	1	1.339	7.046	.009[a]
	Residual	15.963	84	.190		
	Total	17.302	85			
2	Regression	2.258	2	1.129	6.230	.003[b]
	Residual	15.044	83	.181		
	Total	17.302	85			
3	Regression	3.085	3	1.028	5.931	.001[c]
	Residual	14.217	82	.173		
	Total	17.302	85			
4	Regression	3.760	4	.940	5.622	.000[d]
	Residual	13.543	81	.167		
	Total	17.302	85			

5	Regression	3.329	3	1.110	6.512	.001[e]
	Residual	13.973	82	.170		
	Total	17.302	85			
6	Regression	4.314	4	1.078	6.726	.000[f]
	Residual	12.988	81	.160		
	Total	17.302	85			

a. Predictors: (Constant), O28:Better and faster decisions

b. Predictors: (Constant), O28:Better and faster decisions, E14:Stakeholder demands

c. Predictors: (Constant), O28:Better and faster decisions, E14:Stakeholder demands, O25:Customer service excellence

d. Predictors: (Constant), O28:Better and faster decisions, E14:Stakeholder demands, O25:Customer service excellence, T4:Enterprise wide data driven decision making capability

e. Predictors: (Constant), E14:Stakeholder demands, O25:Customer service excellence, T4:Enterprise wide data driven decision making capability

f. Predictors: (Constant), E14:Stakeholder demands, O25:Customer service excellence, T4:Enterprise wide data driven decision making capability, O13:Governance requirements (IT & Corporate)

g. Dependent Variable: Adopt Forecasting

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.386	.135		2.860	.005
	O28:Better and faster decisions	.100	.038	.278	2.654	.009
2	(Constant)	.733	.203		3.614	.001
	O28:Better and faster decisions	.088	.037	.244	2.354	.021
	E14:Stakeholder demands	-.114	.051	-.233	-2.252	.027
3	(Constant)	.445	.238		1.871	.065
	O28:Better and faster decisions	.068	.038	.188	1.805	.075
	E14:Stakeholder demands	-.123	.050	-.252	-2.483	.015
	O25:Customer service excellence	.110	.050	.226	2.183	.032
4	(Constant)	.304	.244		1.245	.217
	O28:Better and faster decisions	.060	.037	.165	1.605	.112
	E14:Stakeholder demands	-.141	.050	-.289	-2.852	.006
	O25:Customer service excellence	.110	.049	.226	2.228	.029
	T4:Enterprise wide data driven decision making capability	.069	.034	.202	2.009	.048
5	(Constant)	.457	.227		2.012	.047
	E14:Stakeholder demands	-.156	.049	-.319	-3.164	.002
	O25:Customer service excellence	.129	.048	.265	2.670	.009
	T4:Enterprise wide data driven decision making capability	.075	.034	.219	2.179	.032

6	(Constant)	.171	.249		.686	.495
	E14:Stakeholder demands	-.177	.049	-.363	-3.650	.000
	O25:Customer service excellence	.130	.047	.268	2.779	.007
	T4:Enterprise wide data driven decision making capability	.082	.033	.242	2.471	.016
	O13:Governance requirements (IT & Corporate)	.116	.047	.243	2.478	.015

a. Dependent Variable: Adopt Forecasting

4.3.5 Regression Analysis on BI drivers against KPI Adoption

Regression analysis on twenty eight drivers against BI KPI adoption was performed. The P-value in ANOVA is 0.515 as shown in Table 26 which is more than 0.05. Therefore, there is no significant relationship between twenty eight drivers and BI forecasting adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There is 32.4% of total of Y (BI KPI adoption) explained by the regression model consisting twenty eight drivers.

Table 26: Regression Analysis Result between twenty eight drivers with BI KPI Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.569[a]	.324	-.008	.500	.324	.976	28	57	.515

Dependent Variable: Adopt KPI

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.830	28	.244	.976	.515[a]
	Residual	14.251	57	.250		
	Total	21.081	85			

Dependent Variable: Adopt KPI

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.736	.691		2.512	.015
	O1:Reduce information analysis cost	-.020	.061	-.045	-.323	.748
	E2:Increase business competitiveness	-.009	.048	-.024	-.182	.856
	O3:Increase profitability	-.016	.049	-.046	-.330	.743
	T4:Enterprise wide data driven decision making capability	.036	.052	.096	.695	.490
	T5:Availability of data analysis tool	-.038	.051	-.101	-.741	.461
	O6:Risk mitigation (Financial or Operational)	-.010	.059	-.024	-.177	.860
	T7:Risk reporting capability	-.057	.059	-.127	-.959	.342
	O8:Optimizaton in resource allocation	-.012	.060	-.032	-.207	.837
	T9:Deeper data insight	.034	.052	.084	.661	.511
	O10:Organisational efficiency (Financial or Operational)	.100	.056	.258	1.788	.079
	E11:Vendor website role in BI buying decision	.042	.080	.067	.527	.600
	T12:Rapid change in data volumes lead to a need for BI	-.072	.059	-.179	-1.213	.230
	O13:Governance requirements (IT & Corporate)	-.054	.067	-.103	-.804	.425
	E14:Stakeholder demands	-.065	.073	-.121	-.893	.375
	T15:Expanding ERP, Enterprise Resource Planning	-.005	.056	-.013	-.087	.931
	T16:Data availability readiness	.001	.059	.002	.019	.985
	T17:Forward-looking view': Forecasting	.001	.052	.002	.014	.989
	O18:Align with corporate strategy	.117	.081	.195	1.444	.154
	O19:Effective decision making at all levels of company	-.061	.055	-.155	-1.106	.274
	O20:Predict market trends	.058	.060	.140	.959	.341
	O21:Improve enterprise performance	-.141	.056	-.366	-2.525	.014
	T22:Single version of truth	-.055	.075	-.102	-.740	.463
	T23:Current and accurate information	-.062	.062	-.146	-.992	.325
	T24:Rapidly change of information needs	.114	.055	.288	2.064	.044
	O25:Customer service excellence	-.045	.073	-.084	-.614	.542
	O26:More efficient service	-.013	.057	-.029	-.225	.823
	O27:Increase service costs	-.119	.089	-.176	-1.334	.187
	O28:Better and faster decisions	-.039	.057	-.097	-.673	.504

Dependent Variable: Adopt KPI

4.3.5.1 Stepwise Regression on BI drivers against KPI Adoption

The regression analysis then extended to stepwise estimation procedure to select the driver/s that has highest bivariate correlation with BI KPI adoption. The first step is to build a regression equation just using a single independent (O21: Improve enterprise performance) which has the highest bivariate correlation. The P-value is 0.011 as shown in Table 27 which is less than 0.05, therefore there is a significant relationship between O21 and BI KPI adoption. R square (R^2) is only 0.074 where has 7.4% of total of Y (BI KPI adoption) explained by the regression model consisting O21.

Table 27: Stepwise Regression Analysis Result for BI KPI Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.272[a]	.074	.063	.482	.074	6.736	1	84	.011

a. Predictors: (Constant), O21:Improve enterprise performance

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.565	1	1.565	6.736	.011[a]
	Residual	19.516	84	.232		
	Total	21.081	85			

a. Predictors: (Constant), O21:Improve enterprise performance

b. Dependent Variable: Adopt KPI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.918	.144		6.381	.000
	O21:Improve enterprise performance	-.105	.040	-.272	-2.595	.011

a. Dependent Variable: Adopt KPI

4.4 Regression Analysis for BI Barriers

Regression analysis was performed to analyse the relationship between twenty barriers and BI adoptions. The objective of this analysis is to use the twenty barriers as independent variables to predict each individual BI adoption as the single dependent value. Extended analysis of stepwise estimation procedure also was conducted to maximise the incremental explained variance at each step of model building. The highest bivariate correlation with the BI each individual adoption will be selected.

4.4.1 Regression Analysis on BI barriers against Reporting Adoption

First of all, a regression analysis on twenty barriers against BI reporting adoption was carried out. Based on analysis result as shown in Table 28, the P-value in ANOVA is 0.574 which is more than 0.05. Therefore, there is no significant relationship between twenty barriers and BI reporting adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There is 21.9% of total of Y (BI reporting adoption) explained by the regression model consisting twenty barriers.

Table 28: Summary of Regression Analysis between twenty barriers with BI Reporting Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.468[a]	.219	-.021	.437	.219	.912	20	65	.574

Dependent Variable: Adopt Reporting

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.478	20	.174	.912	.574[a]
	Residual	12.394	65	.191		
	Total	15.872	85			

Dependent Variable: Adopt Reporting

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.038	.635		-.059	.953
	BO1: Upfront costs	-.007	.054	-.016	-.129	.897
	BO2: Setup costs	.109	.063	.217	1.720	.090
	BO3: Running costs	.096	.065	.192	1.491	.141
	BT4: Lack of skills to implement BI / Data Warehouse	-.060	.065	-.124	-.927	.357
	BO5: Lack of executive board interest	.010	.049	.026	.203	.840
	BO6: No real or tangible benefits	-.097	.045	-.277	-2.151	.035
	BO7: Poor Return of Investment (ROI)	.026	.043	.074	.601	.550
	BO8: Lack of knowledge about BI products	.006	.052	.017	.124	.902
	BT9: Lack of technology (pre-BI infrastructure)	.066	.050	.168	1.312	.194
	BT10: Data security concerns (Pervasive BI and Outsourced version)	-.048	.052	-.116	-.925	.358
	BE11: Insufficient government support for BI initiatives	-.016	.042	-.045	-.374	.709
	BE12: Lack of a complete BI Suite offering by any vendor	.068	.063	.153	1.076	.286
	BE13: Typical BI systems not optimized for OLTP	-.042	.066	-.086	-.643	.523
	BT14: Frequent data latency issues	.005	.056	.011	.089	.929
	BO15: Implementation time lags	-.079	.056	-.188	-1.418	.161
	BT16: BI project complexity	.030	.046	.080	.645	.521
	BO17: High costs of OLAP based systems (BI tuned)	-.026	.050	-.063	-.509	.612
	BT18: BI tools highly specialized for wide spread use	.099	.060	.208	1.660	.102
	BT19: Complexities of data management	.025	.047	.065	.533	.596
	BT20: Fragmented data sources in the enterprise	.061	.052	.162	1.174	.245

Dependent Variable: Adopt Reporting

4.4.1.1 Stepwise Regression on BI barriers against Reporting Adoption

The regression analysis then extended to stepwise estimation procedure to select the barrier/s that has highest bivariate correlation with BI reporting adoption. Based on result derived, there was no significant variable should be entered into stepwise regression equation.

4.4.2 Regression Analysis on BI barriers against Statistical Adoption

Regression analysis on twenty barriers against BI statistical adoption was performed. As shown in Table 29, the P-value in ANOVA is 0.951 which is more than 0.05. Therefore, there is no significant relationship between twenty barriers and BI statistical adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There was 13.6% of total of Y (BI statistical adoption) explained by the regression model consisting twenty barriers.

Table 29: Summary of Regression Analysis between twenty barriers with BI Statistical Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.369[a]	.136	-.129	.459	.136	.513	20	65	.951

Dependent Variable: Adopt Statistical

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.163	20	.108	.513	.951[a]
	Residual	13.709	65	.211		
	Total	15.872	85			

Dependent Variable: Adopt Statistical

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.281	.668		.422	.675
	BO1: Upfront costs	.007	.057	.016	.128	.898
	BO2: Setup costs	.000	.067	-.002	-.012	.991
	BO3: Running costs	.052	.068	.103	.762	.449
	BT4: Lack of skills to implement BI / Data Warehouse	.136	.068	.281	1.993	.051
	BO5: Lack of executive board interest	-.024	.052	-.062	-.460	.647
	BO6: No real or tangible benefits	.041	.047	.118	.870	.388
	BO7: Poor Return of Investment (ROI)	.034	.045	.096	.744	.459
	BO8: Lack of knowledge about BI products	.043	.055	.111	.778	.439

BT9: Lack of technology (pre-BI infrastructure)	-.008	.053	-.020	-.152	.880
BT10: Data security concerns (Pervasive BI and Outsourced version)	.001	.055	.003	.025	.980
BE11: Insufficient government support for BI initiatives	-.003	.045	-.008	-.060	.952
BE12: Lack of a complete BI Suite offering by any vendor	-.060	.066	-.137	-.912	.365
BE13: Typical BI systems not optimized for OLTP	.039	.069	.078	.557	.580
BT14: Frequent data latency issues	.005	.059	.011	.082	.935
BO15: Implementation time lags	.016	.058	.038	.276	.784
BT16: BI project complexity	-.048	.049	-.129	-.989	.326
BO17: High costs of OLAP based systems (BI tuned)	-.017	.053	-.043	-.329	.743
BT18: BI tools highly specialized for wide spread use	-.034	.063	-.072	-.543	.589
BT19: Complexities of data management	.012	.049	.031	.244	.808
BT20: Fragmented data sources in the enterprise	-.063	.055	-.168	-1.159	.251

Dependent Variable: Adopt Statistical

4.4.2.1 Stepwise Regression on BI barriers against Statistical Adoption

The regression analysis then extended to stepwise estimation procedure to select the barrier/s that has highest bivariate correlation with BI statistical adoption. As shown in Table 30, the first step was to build a regression equation just using a single independent (BT4: Lack of skills to implement BI / Data Warehouse). The P-value in ANOVA is 0.017 which is less than 0.05, therefore there is a significant relationship between BT4 and BI statistical adoption.

Table 30: Stepwise Regression Analysis Result for BI Statistical Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.257[a]	.066	.055	.420	.066	5.937	1	84	.017

a. Predictors: (Constant), BT4: Lack of skills to implement BI / Data Warehouse

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.048	1	1.048	5.937	.017[a]
	Residual	14.824	84	.176		
	Total	15.872	85			

a. Predictors: (Constant), BT4: Lack of skills to implement BI / Data Warehouse

b. Dependent Variable: Adopt Statistical

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.303	.191		1.588	.116
	BT4: Lack of skills to implement BI / Data Warehouse	.124	.051	.257	2.437	.017

a. Dependent Variable: Adopt Statistical

4.4.3 Regression Analysis on BI barriers against Decision Making Adoption

Regression analysis on twenty barriers against BI decision making adoption was performed. The overall P-value is 0.435 as shown in Table 31 which is more than 0.05. Therefore, there is no significant relationship between twenty barriers and BI decision making adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There is 49.2% of total of Y (BI decision making adoption) explained by the regression model consisting of twenty barriers.

Table 31: Summary of Regression Analysis between twenty barriers with BI Decision Making Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.492[a]	.242	.009	.437	.242	1.037	20	65	.435

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.961	20	.198	1.037	.435[a]
	Residual	12.411	65	.191		
	Total	16.372	85			

b. Dependent Variable: Adopt Decision Making

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.483	.635		2.334	.023
	BO1: Upfront costs	.023	.054	.051	.431	.668
	BO2: Setup costs	.007	.063	.013	.108	.914
	BO3: Running costs	.069	.065	.135	1.070	.289
	BT4: Lack of skills to implement BI / Data Warehouse	-.062	.065	-.126	-.957	.342
	BO5: Lack of executive board interest	-.045	.049	-.115	-.911	.366
	BO6: No real or tangible benefits	-.060	.045	-.169	-1.334	.187
	BO7: Poor Return of Investment (ROI)	-.023	.043	-.065	-.536	.594
	BO8: Lack of knowledge about BI products	.018	.052	.047	.353	.725
	BT9: Lack of technology (pre-BI infrastructure)	-.011	.050	-.029	-.226	.822
	BT10: Data security concerns (Pervasive BI and Outsourced version)	.078	.052	.186	1.507	.137
	BE11: Insufficient government support for BI initiatives	-.017	.042	-.048	-.404	.688
	BE12: Lack of a complete BI Suite offering by any vendor	-.025	.063	-.055	-.395	.694
	BE13: Typical BI systems not optimized for OLTP	-.037	.066	-.073	-.557	.579
	BT14: Frequent data latency issues	-.017	.056	-.037	-.295	.769
	BO15: Implementation time lags	.052	.056	.122	.934	.354
	BT16: BI project complexity	-.078	.046	-.207	-1.691	.096
	BO17: High costs of OLAP based systems (BI tuned)	-.048	.050	-.117	-.962	.339

	BT18: BI tools highly specialized for wide spread use	.011	.060	.023	.186	.853
	BT19: Complexities of data management	.048	.047	.124	1.029	.307
	BT20: Fragmented data sources in the enterprise	-.114	.052	-.297	-2.188	.032

a. Dependent Variable: Adopt Decision Making

4.4.3.1 Stepwise Regression on BI barriers against Decision Making Adoption

The regression analysis then extended to stepwise estimation procedure to select the barrier/s that has highest bivariate correlation with BI decision making adoption. Based on result derived, there was no significant variable should be entered into stepwise regression equation.

4.4.4 Regression Analysis on BI barriers against Forecasting Adoption

Regression analysis on twenty barriers against BI forecasting adoption was performed. The overall P-value is 0.958 as shown in Table 32 which is more than 0.05. Therefore, there is no significant relationship between twenty barriers and BI forecasting adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There is 13.3% of total of Y (BI forecasting adoption) explained by the regression model consisting of twenty barriers.

Table 32: Summary of Regression Analysis between twenty barriers with BI Forecasting Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.364[a]	.133	-.134	.480	.133	.498	20	65	.958

Dependent Variable: Adopt Forecasting

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.298	20	.115	.498	.958[a]
	Residual	15.004	65	.231		
	Total	17.302	85			

Dependent Variable: Adopt Forecasting

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.595	.698		.852	.397
	BO1: Upfront costs	.014	.059	.030	.235	.815
	BO2: Setup costs	-.038	.070	-.073	-.552	.583
	BO3: Running costs	.063	.071	.120	.885	.380
	BT4: Lack of skills to implement BI / Data Warehouse	-.027	.071	-.053	-.377	.707
	BO5: Lack of executive board interest	.014	.054	.035	.257	.798
	BO6: No real or tangible benefits	-.006	.050	-.018	-.131	.896
	BO7: Poor Return of Investment (ROI)	-.020	.048	-.056	-.431	.668
	BO8: Lack of knowledge about BI products	.092	.057	.228	1.603	.114
	BT9: Lack of technology (pre-BI infrastructure)	.042	.055	.101	.751	.455
	BT10: Data security concerns (Pervasive BI and Outsourced version)	-.008	.057	-.019	-.140	.889
	BE11: Insufficient government support for BI initiatives	-.063	.047	-.171	-1.347	.183
	BE12: Lack of a complete BI Suite offering by any vendor	.019	.069	.042	.277	.782
	BE13: Typical BI systems not optimized for OLTP	-.015	.072	-.029	-.208	.836
	BT14: Frequent data latency issues	-.009	.062	-.020	-.148	.883
	BO15: Implementation time lags	-.065	.061	-.149	-1.064	.291
	BT16: BI project complexity	-.004	.051	-.011	-.080	.936
	BO17: High costs of OLAP based systems (BI tuned)	.046	.055	.109	.835	.407
	BT18: BI tools highly specialized for wide spread use	.025	.066	.051	.384	.702

BT19: Complexities of data management	-.012	.052	-.030	-.231	.818
BT20: Fragmented data sources in the enterprise	.000	.057	.000	-.004	.997

a. Dependent Variable: Adopt Forecasting

4.4.4.1 Stepwise Regression on BI barriers against Forecasting Adoption

The regression analysis then extended to stepwise estimation procedure to select the barrier/s that has highest bivariate correlation with BI forecasting adoption. Based on result derived, there was no significant variable should be entered into stepwise regression equation.

4.4.5 Regression Analysis on BI barriers against KPI Adoption

Regression analysis on twenty barriers against BI forecasting adoption was performed. The overall P-value is 0.484 as shown in Table 33 which is more than 0.05. Therefore, there is no significant relationship between twenty barriers and BI KPI adoption.

R square (R^2) is defined as the correlation coefficient squared and also referring to coefficient of determination. There is 23.4% of total of Y (BI KPI adoption) explained by the regression model consisting of twenty barriers.

Table 33: Summary of Regression Analysis between twenty barriers with BI KPI Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.483[a]	.234	-.002	.499	.234	.991	20	65	.484

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.928	20	.246	.991	.484[a]
	Residual	16.154	65	.249		
	Total	21.081	85			

b. Dependent Variable: Adopt KPI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.054	.725		-.075	.941
	BO1: Upfront costs	.050	.062	.096	.806	.423
	BO2: Setup costs	-.073	.072	-.126	-1.012	.315
	BO3: Running costs	-.070	.074	-.120	-.944	.349
	BT4: Lack of skills to implement BI / Data Warehouse	.093	.074	.168	1.263	.211
	BO5: Lack of executive board interest	.057	.056	.128	1.006	.318
	BO6: No real or tangible benefits	-.028	.051	-.070	-.552	.583
	BO7: Poor Return of Investment (ROI)	-.005	.049	-.013	-.103	.918
	BO8: Lack of knowledge about BI products	-.026	.059	-.059	-.442	.660
	BT9: Lack of technology (pre-BI infrastructure)	.005	.058	.012	.094	.925
	BT10: Data security concerns (Pervasive BI and Outsourced version)	-.008	.059	-.017	-.136	.892
	BE11: Insufficient government support for BI initiatives	.023	.048	.056	.467	.642
	BE12: Lack of a complete BI Suite offering by any vendor	.061	.072	.120	.851	.398
	BE13: Typical BI systems not optimized for OLTP	-.126	.075	-.223	-1.682	.097
	BT14: Frequent data latency issues	.002	.064	.004	.030	.976
	BO15: Implementation time lags	.089	.063	.185	1.408	.164
	BT16: BI project complexity	.077	.053	.180	1.461	.149
	BO17: High costs of OLAP based systems (BI tuned)	-.034	.057	-.072	-.592	.556
	BT18: BI tools highly specialized for wide spread use	.014	.068	.025	.205	.838
	BT19: Complexities of data management	-.043	.054	-.097	-.798	.428
	BT20: Fragmented data sources in the enterprise	.135	.059	.310	2.271	.026

a. Dependent Variable: Adopt KPI

4.4.5.1 Stepwise Regression on BI barriers against KPI Adoption

The regression analysis then extended to stepwise estimation procedure to select the barrier/s that has highest bivariate correlation with BI KPI adoption. As shown in Table 34, the first step was to build a regression equation just using a single independent (BO15: Implementation time lags). The P-value in ANOVA is 0.022 which is less than 0.05, therefore there is a significant relationship between BO15 and BI KPI adoption.

Table 34: Stepwise Regression Analysis Result for BI KPI Adoption

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.246[a]	.061	.050	.486	.061	5.427	1	84	.022

a. Predictors: (Constant), BO15: Implementation time lags

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.279	1	1.279	5.427	.022[a]
	Residual	19.802	84	.236		
	Total	21.081	85			

a. Predictors: (Constant), BO15: Implementation time lags

b. Dependent Variable: Adopt KPI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.188	.172		1.090	.279
	BO15: Implementation time lags	.119	.051	.246	2.330	.022

a. Dependent Variable: Adopt KPI

4.5 Summary of Regression Analysis Result

Based on the regression analysis performed, the significant drivers and barriers are identified as shown in Table 35. Among the nine drivers identified, driver O28 (Better and faster decisions) was significantly related to both BI reporting adoption and decision making adoption. On contrary, only two barriers were significantly related to BI adoption among the twenty barriers.

In order to further analyse the relationship between these drivers/barriers and BI adoption, one-way ANOVA was selected which can analyse the one-to-one relationship more accurately.

Table 35: Summary of Significant Drivers and Barriers discovered in Regression Analysis

BI Adoption	Significant Drivers	Significant Barriers
Reporting	O28: Better and faster decisions	-
Statistical	O20: Predict market trends	BT4: Lack of skills to implement BI / Data Warehouse
Decision Making	O28: Better and faster decisions T22: Single version of truth O19: Effective decision making at all levels of company	-
Forecasting	E14: Stakeholder demands O25: Customer service excellence T4: Enterprise wide data driven decision making capability O13: :Governance requirements (IT & Corporate)	-
KPI	O21: :Improve enterprise performance	BO15: Implementation time lags

4.6 One-way ANOVA Analysis for BI drivers

One-way ANOVA analysis was carried out to further examine the relationship between BI drivers with BI adoption. This analysis only focus on the drivers as proven significantly related to respective BI module adoption in regression analysis performed.

4.6.1 BI Reporting Adoption

Only a driver, O28 (Better and faster decisions) was proven significant related to BI reporting adoption. Hence, only this driver was selected for one-way ANOVA analysis to further examine the relationship between the driver and BI reporting adoption.

4.6.1.1 One-way ANOVA for O28: Better and faster decisions

One-way ANOVA was performed to analyse the relationship between O28 (Better and faster decision) and BI reporting adoption. The P-value is 0.000 as shown in Table 36 which is less than 0.05, therefore O28 is significantly related to BI reporting adoption.

Table 36: One-way ANOVA between O28 and BI Reporting Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3.685	4	.921	6.123	.000
Within Groups	12.187	81	.150		
Total	15.872	85			

4.6.2 BI Statistical Adoption

Only a driver, O20 (Predict market trends) was proven significant related to BI statistical adoption. Hence, only this driver was selected for one-way ANOVA analysis to further examine the relationship between the driver and BI statistical adoption.

4.6.2.1 One-way ANOVA for O20: Predict market trends

One-way ANOVA was performed to analyse the relationship between O20 (Predict market trends) and BI statistical adoption. The P-value is 0.080 as shown in Table 37 which is more than 0.05, therefore O20 is not significantly related to BI statistical adoption.

Table 37: One-way ANOVA between O20 and BI Statistical Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.534	4	.383	2.166	.080
Within Groups	14.338	81	.177		
Total	15.872	85			

4.6.3 BI Decision Making Adoption

There are three drivers, O28 (Better and faster decisions), T22 (Single version of truth) and O19 (Effective decision making at all levels of company), were proven significant related to BI decision making adoption. Hence, only these drivers were selected for one-way ANOVA analysis to further examine the relationship between the drivers and BI decision making adoption.

4.6.3.1 One-way ANOVA for O28: Better and faster decisions

One-way ANOVA was performed to analyse the relationship between O28 (Better and faster decisions) and BI decision making adoption. The P-value is 0.119 as shown in Table 38 which is more than 0.05, therefore O28 is not significantly related to BI decision making adoption.

Table 38: One-way ANOVA between O28 and BI Decision Making Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.402	4	.350	1.896	.119
Within Groups	14.970	81	.185		
Total	16.372	85			

4.6.3.2 One-way ANOVA for T22: Single version of truth

One-way ANOVA was performed to analyse the relationship between T22 (Single version of truth) and BI decision making adoption. The P-value is 0.035 as shown in Table 39 which is less than 0.05, therefore T22 is significantly related to BI decision making adoption.

Table 39: One-way ANOVA between T22 and BI Decision Making Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.622	3	.541	3.006	.035
Within Groups	14.750	82	.180		
Total	16.372	85			

4.6.3.3 One-way ANOVA for O19: Effective decision making at all levels of company

One-way ANOVA was performed to analyse the relationship between O19 (Effective decision making at all levels of company) and BI decision making adoption. The P-value is 0.027 as shown in Table 40 which is less than 0.05, therefore O19 is significantly related to BI decision making adoption.

Table 40: One-way ANOVA between O19 and BI Decision Making Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.053	4	.513	2.904	.027
Within Groups	14.319	81	.177		
Total	16.372	85			

4.6.4 BI Forecasting Adoption

There are four drivers, E14 (Stakeholder demands), O25 (Customer service excellence), T4 (Enterprise wide data driven decision making capability) and O13 (Governance requirements (IT & Corporate)), were proven significant related to BI forecasting adoption. Hence, only these drivers were selected for one-way

ANOVA analysis to further examine the relationship between the drivers and BI forecasting adoption.

4.6.4.1 One-way ANOVA for E14: Stakeholder demands

One-way ANOVA was performed to analyse the relationship between E14 (Stakeholder demands) and BI forecasting adoption. As shown in Table 41, the P-value is 0.023 which is less than 0.05. Therefore E14 is significantly related to BI forecasting adoption.

Table 41: One-way ANOVA between E14 and BI Forecasting Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.895	3	.632	3.362	.023
Within Groups	15.407	82	.188		
Total	17.302	85			

4.6.4.2 One-way ANOVA for O25: Customer service excellence

One-way ANOVA was performed to analyse the relationship between O25 (Customer service excellence) and BI forecasting adoption. The P-value is 0.053as shown in Table 42 which is more than 0.05, therefore O25 is not significantly related to BI forecasting adoption.

Table 42: One-way ANOVA between O25 and BI Forecasting Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.540	3	.513	2.671	.053
Within Groups	15.762	82	.192		
Total	17.302	85			

4.6.4.3 One-way ANOVA for T4: Enterprise wide data driven decision making capability

One-way ANOVA was performed to analyse the relationship between T4 (Enterprise wide data driven decision making capability) and BI forecasting adoption. As shown in Table 43, the P-value is 0.351 which is more than 0.05. Therefore T4 is not significantly related to BI forecasting adoption.

Table 43: One-way ANOVA between T4 and BI Forecasting Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.910	4	.227	1.124	.351
Within Groups	16.392	81	.202		
Total	17.302	85			

4.6.4.4 One-way ANOVA for O13: Governance requirements (IT & Corporate)

One-way ANOVA was performed to analyse the relationship between O13 (Governance requirement (IT & Corporate)) and BI forecasting adoption. As shown in Table 44, the P-value is 0.253 which is more than 0.05. Therefore O13 is not significantly related to BI forecasting adoption.

Table 44: One-way ANOVA between O13 and BI Forecasting Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.836	3	.279	1.387	.253
Within Groups	16.467	82	.201		
Total	17.302	85			

4.6.5 BI KPI Adoption

Only a driver, O21 (Improve enterprise performance) was proven significant related to BI KPI adoption. Hence, only this driver was selected for one-way ANOVA analysis to further examine the relationship between the driver and BI KPI adoption.

4.6.5.1 One-way ANOVA for O21: Improve enterprise performance

One-way ANOVA was performed to analyse the relationship between O21 (Improve enterprise performance) and BI KPI adoption. As shown in Table 45, the P-value is 0.076 which is more than 0.05. Therefore O21 is not significantly related to BI KPI adoption.

Table 45: One-way ANOVA between O21 and BI KPI Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.068	4	.517	2.202	.076
Within Groups	19.013	81	.235		
Total	21.081	85			

4.7 One-way ANOVA Analysis for BI barriers

One-way ANOVA analysis was carried out to further examine the relationship between BI barriers with BI adoption. This analysis only focus on the barriers as proven significantly related to respective BI module adoption in regression analysis performed.

4.7.1 BI Statistical Adoption

Only a barrier, O20 (Predict market trends) was proven significant related to BI statistical adoption. Hence, only this driver was selected for one-way ANOVA analysis to further examine the relationship between the driver and BI statistical adoption.

4.7.1.1 One-way ANOVA for BT4: Lack of skills to implement BI / Data Warehouse

One-way ANOVA was performed to analyse the relationship between BT4 (Lack of skills to implement BI / Data Warehouse) and BI statistical adoption. As shown in Table 46, the P-value is 0.588 which is more than 0.05. Therefore BT4 is not significantly related to BI statistical adoption.

Table 46: One-way ANOVA between BT4 and BI Statistical Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.475	3	.825	.645	.588
Within Groups	104.828	82	1.278		
Total	107.302	85			

4.7.2 BI KPI Adoption

Only a barrier, BO15 (Implementation time lags) was proven significant related to BI KPI adoption. Hence, only this barrier was selected for one-way ANOVA analysis to further examine the relationship between the barrier and BI KPI adoption.

4.7.2.1 One-way ANOVA for BO15: Implementation time lags

One-way ANOVA was performed to analyse the relationship between BO15 (Implementation time lags) and BI KPI adoption. As shown in Table 47, the P-value is 0.076 which is more than 0.05. Therefore BO15 is not significantly related to BI KPI adoption.

Table 47: One-way ANOVA between BO15 and BI KPI Adoption

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	9.056	4	2.264	1.867	.124
Within Groups	98.246	81	1.213		
Total	107.302	85			

4.8 Summary of One-way ANOVA Analysis Result

Based on the One-way ANOVA analysis performed, the significant drivers and barriers are identified as shown in Table 48. There were only five drivers significantly related to BI module adoption where non barrier was identified.

Table 48: Summary of Significant Drivers and Barriers based on Regression Analysis and One-way ANOVA

BI Adoption	Significant Drivers	Significant Barriers
Reporting	O28: Better and faster decisions	-
Statistical	-	-
Decision Making	T22: Single version of truth O19: Effective decision making at all levels of company	-
Forecasting	E14: Stakeholder demands	-
KPI	-	-

CHAPTER 5

DISCUSSION AND CONCLUSION

5.1 Introduction

This chapter discusses the implication of the findings presented in the Chapter Four. The first section presents the summary of findings for the main hypotheses as formulated in Chapter Two and discussion to explain the possibilities of their junction or disjunction with the literatures. The second section describes the overall conclusions, research and implications of the study. The third section highlights the limitations of study, implications to methodology, and recommendations for future advices within the contexts of BI adoption in Malaysia.

5.2 Discussion of Findings

The discussion of findings had been carried by responding to the five hypotheses as formulated in Chapter Two. Heppner and Heppner (2004) advised that the discussion the results of each hypothesis may improve the understanding on results of each hypothesis in return.

As described by Heppner and Heppner (2004):
“The data are always friendly. Thus, no matter what you find in your research and whether or not it is expected or contrary to predictions, the data are important to the knowledge base. Thus, rather than feeling disappointed about the findings and

thus perhaps avoiding writing the discussion chapter, you should view all data as friendly and try to understand and discuss the results" (p.328).

The discussion was extended to the relationship between each independent variable with each BI module adoption which has discovered in the analysis.

5.2.1 Discussion on BI Reporting Adoption (Hypothesis 1)

Hypothesis 1

H_0: There is no significant relationship between BI reporting adoption and drivers/barriers.

H_1: There is a significant relationship between BI reporting adoption and drivers/barriers.

Based on the regression analysis performed, there was no significant relationship between BI drivers/barriers and reporting adoption where the overall P-value in ANOVA (regression analysis with 'Enter' method) is greater than 0.05. Therefore, the statement of H_0 in Hypothesis 1 was accepted.

In extended analysis, only a driver (O28: Better and faster decisions) was entered into regression stepwise procedure with overall P-value less than 0.05. Hence, a sub-hypothesis was formulated as below to test the relationship.

Hypothesis 1.1

H_0: There is no significant relationship between BI reporting adoption and O28 (Better and faster decision).

$H_{1.1}$: There is a significant relationship between BI reporting adoption and O28 (Better and faster decision).

The significant relationship between driver O28 and BI reporting adoption was proven by one-way ANOVA analysis result of P-value less than 0.05. Hence, the H_0 in Hypothesis 1.1 was rejected.

5.2.2 Discussion on BI Statistical Adoption (Hypothesis 2)

Hypothesis 2

H_0: There is no significant relationship between BI statistical adoption and drivers/barriers.

H_2: There is a significant relationship between BI statistical adoption and drivers/barriers.

Based on the regression analysis performed, there was no significant relationship between BI drivers/barriers and statistical adoption where the overall P-value in ANOVA (regression analysis with 'Enter' method) is greater than 0.05. Therefore, the statement of H_0 was accepted where there was zero-related between BI statistical adoption and a set of independent variables.

In extended analysis, a driver (O20: Predict market trends) and a barrier (BT4: Lack of skills to implement BI / Data Warehouse) were entered into regression stepwise procedure with overall P-value less than 0.05. Hence, two sub-hypothesis was formulated as below to test the relationship.

Hypothesis 2.1

H_0: There is no significant relationship between BI statistical adoption and O20 (Predict market trends).

$H_{2.1}$: There is a significant relationship between BI statistical adoption and O20 (Predict market trends).

Hypothesis 2.2

H_0: There is no significant relationship between BI statistical adoption and BT4 (Lack of skills to implement BI / Data Warehouse).

$H_{2.2}$: There is a significant relationship between BI statistical adoption and BT4 (Lack of skills to implement BI / Data Warehouse).

The non-significant relationship between driver O20 and BI statistical adoption was proven by one-way ANOVA analysis result of P-value more than 0.05. Hence, the H_0 in Hypothesis 2.1 was accepted.

The non-significant relationship between barrier BT4 and BI statistical adoption was proven by one-way ANOVA analysis result of P-value more than 0.05. Hence, the H_0 in Hypothesis 2.2 was accepted.

5.2.3 Discussion on BI Decision Making Adoption (Hypothesis 3)

Hypothesis 3

H_0: There is no significant relationship between BI decision making adoption and drivers/barriers.

H_3: There is a significant relationship between BI decision making adoption and drivers/barriers.

Based on the regression analysis performed, there was no significant relationship between BI drivers/barriers and decision making adoption where the overall P-value in ANOVA (regression analysis with 'Enter' method) is greater than 0.05. Therefore, the statement of H_0 was accepted.

In extended analysis, there were three drivers (O28: Better and faster decisions, T22: Single version of truth and O19: Effective decision making at all levels of company) entered into regression stepwise procedure with overall P-value less than 0.05. Hence, three sub-hypothesis were formulated as below to test their relationship.

Hypothesis 3.1

H_0: There is no significant relationship between BI decision making adoption and O28 (Better and faster decisions).

$H_{3.1}$: There is a significant relationship between BI decision making adoption and O28 (Better and faster decisions).

Hypothesis 3.2

H_0: There is no significant relationship between BI decision making adoption and T22 (Single version of truth).

$H_{3.2}$: There is a significant relationship between BI decision making adoption and T22 (Single version of truth).

Hypothesis 3.3

H_0: There is no significant relationship between BI decision making adoption and O19 (Effective decision making at all levels of company).

$H_{3.3}$: There is a significant relationship between BI decision making adoption and O19 (Effective decision making at all levels of company).

The non-significant relationship between driver O28 and BI decision making adoption was proven by one-way ANOVA analysis result of P-value more than 0.05. Hence, the H_0 in Hypothesis 3.1 was accepted.

The significant relationship between driver T22 and BI decision making adoption was proven by one-way ANOVA analysis result of P-value less than 0.05. Hence, the H_0 in Hypothesis 3.2 was rejected.

The significant relationship between driver O19 and BI decision making adoption was proven by one-way ANOVA analysis result of P-value less than 0.05. Hence, the H_0 in Hypothesis 3.3 was rejected.

5.2.4 Discussion on BI Forecasting Adoption (Hypothesis 4)

Hypothesis 4

H_0: There is no significant relationship between BI forecasting adoption and drivers/barriers.

H_4: There is a significant relationship between BI forecasting adoption and drivers/barriers.

Based on the regression analysis performed, there was no significant relationship between BI drivers/barriers and forecasting adoption where the overall P-value in ANOVA (regression analysis with ‘Enter’ method) is greater than 0.05. Therefore, the statement of H_0 was accepted.

In extended analysis, there were four drivers (E14: Stakeholder demands, O25: Customer service excellence, T4: Enterprise wide data driven decision making capability and O13: Governance requirements (IT & Corporate)) entered into regression stepwise procedure with overall P-value less than 0.05. Hence, four sub-hypothesis were formulated as below to test their relationship.

<u>Hypothesis 4.1</u>

H_0: There is no significant relationship between BI forecasting adoption and E14 (Stakeholder demands).

$H_{4.1}$: There is a significant relationship between BI forecasting adoption and E14 (Stakeholder demands).

<u>Hypothesis 4.2</u>

H_0: There is no significant relationship between BI forecasting adoption and O25 (Customer service excellence).

$H_{4.2}$: There is a significant relationship between BI forecasting adoption and O25 (Customer service excellence).

<u>Hypothesis 4.3</u>

H_0: There is no significant relationship between BI forecasting adoption and T4 (Enterprise wide data driven decision making capability).

$H_{4.3}$: There is a significant relationship between BI forecasting adoption and T4 (Enterprise wide data driven decision making capability).

<u>Hypothesis 4.4</u>

H_0: There is no significant relationship between BI forecasting adoption and O13 (Governance requirements (IT & Corporate)).

$H_{4.4}$: There is a significant relationship between BI forecasting adoption and O13 (Governance requirements (IT & Corporate)).

The significant relationship between driver E14 and BI forecasting adoption was proven by one-way ANOVA analysis result of P-value less than 0.05. Hence, the H_0 in Hypothesis 4.1 was rejected.

The non-significant relationship between driver O25 and BI forecasting adoption was proven by one-way ANOVA analysis result of P-value more than 0.05. Hence, the H_0 in Hypothesis 4.2 was accepted.

The non-significant relationship between driver T4 and BI forecasting adoption was proven by one-way ANOVA analysis result of P-value more than 0.05. Hence, the H_0 in Hypothesis 4.3 was accepted.

The non-significant relationship between driver O13 and BI forecasting adoption was proven by one-way ANOVA analysis result of P-value more than 0.05. Hence, the H_0 in Hypothesis 4.4 was accepted.

5.2.5 Discussion on BI KPI Adoption (Hypothesis 5)

Hypothesis 5

H_0: There is no significant relationship between BI KPI adoption and drivers/barriers.

H_5: There is a significant relationship between BI KPI adoption and drivers/barriers.

Based on the regression analysis performed, there was no significant relationship between BI drivers/barriers and KPI adoption where the overall P-value in ANOVA (regression analysis with 'Enter' method) is greater than 0.05. Therefore, the statement of H_0 was accepted.

In extended analysis, there were a driver (O21: Improve enterprise performance) and a barrier (BO15: Implementation time lags) entered into regression stepwise procedure with overall P-value less than 0.05. Hence, tow sub-hypothesis were formulated as below to test their relationship.

Hypothesis 5.1

H_0: There is no significant relationship between BI KPI adoption and O21 (Improve enterprise performance).

$H_{5.1}$: There is a significant relationship between BI KPI adoption and O21 (Improve enterprise performance).

Hypothesis 5.2

H_0: There is no significant relationship between BI KPI adoption and BO15 (Implementation time lags).

$H_{5.2}$: There is a significant relationship between BI KPI adoption and BO15 (Implementation time lags).

The non-significant relationship between driver O21 and BI KPI adoption was proven by one-way ANOVA analysis result of P-value more than 0.05. Hence, the H_0 in Hypothesis 5.1 was accepted.

The non-significant relationship between barrier BO15 and BI KPI adoption was proven by one-way ANOVA analysis result of P-value more than 0.05. Hence, the H_0 in Hypothesis 5.2 was accepted.

5.3 Overall Conclusions

This research study prevails the BI adoption level in Malaysia was above average where the module adoptions scored from range of 56.98% to 75.58% respectively by referring to Figure 12. BI reporting and statistical adoption have achieved the highest adoption level where BI KPI adoption has scored the lowest. The BI solutions has implemented at departmental level and expected to be move forward to corporate for its fullest benefits utilisation. In overall, the BI adoption in Malaysia was encouraging but yet to accomplish its stabilisation across the corporate. This has answered the research question item one ('What are the adoption levels in Malaysia?') and research objective item one ('Identify the BI adoption levels in Malaysia.') as defined in Chapter 1.

Throughout this research study, we may conclude the BI drivers/barriers identified were not essentially impacting the corporate decision to adopt BI modules. The BI modules are inclusive of reporting, statistical, decision making, forecasting and KPI. This has responded on the research question item two ('What are the correlation between BI adoption and driver/barriers of implementing BI in Malaysia?') and research objective item two ('To analyse the correlated between BI adoption and drivers/barriers of implementing BI in Malaysia.').

Among these five BI modules, only three of them have identified their significant drivers and non significant barrier was spotted in this research study. This has achieved the research objective of 'Identify the significant drivers and barriers of BI adoption in Malaysia' (item three) as well as the research question of 'What are the significant drivers and barriers of BI adoption in Malaysia?' (item three).

The study has shown the major corporate were implementing BI reporting in departmental level towards having better and faster decisions. Eventually, some of the corporate has started utilise BI reporting in corporate level to provide better overall pictures for decision making.

Corporate executives essentially wanted to achieve single version of truth and effective decision making at all levels of company by adopting BI decision making. Unfortunately, the BI decision making only make used at department level in majority corporate where still has distance from effective decision making at all levels of company.

The stakeholder's demands drive the corporate to implement BI forecasting at least at departmental level for a better future projection of the businesses or operations. Like other BI modules mentioned above, some of the corporate has achieved the corporate level usage for BI forecasting.

By evaluating the analysis result between descriptive and regression, the drivers scored the top three highest mean in description were not significantly correlated to any BI module adoption in regression. On other hand, the drivers scored the top lowest mean in description were significantly correlated to one of the BI module adoption although driver O13 (Governance requirements (IT & Corporate)) was proven not a significant driver in one-way ANOVA analysis. Due to non barriers was identified in regression and one-way ANOVA, consequently the barriers scored the top three highest and lowest mean were not significantly correlated to any BI module adoption. In summary, the mean scoring of drivers and barriers was not guaranteed the significant relationship with BI module adoption.

5.4 Implications of the Study

This research study on BI adoption has filling up the gap in the present researches which only emphasised the general technology or ERP application adoption as specified in Chapter 1.2 Problem Statement. Hence, this has contributing to the literature on BI adoption as a great reference for the business executives. and increasing the probability to be accepted by corporate

The results derived from this research study have provided assistance to executives to have better understanding of drivers and barriers towards BI adoption in a corporate. Although the overall drivers and barriers were not significant related to any BI module adoption, but the significant drivers were identified throughout the complete analysis. By knowing the significant drivers for respective BI module, executives may include the related information into their business proposal prepared prior to convince management for the adoption. It is vital for the executives to have correct direction by scoping down the research area which has resolving the huge research scope problem as defined in problem statement.

Although no significant barrier was identified in this research project, but it is a good beginning for the executives to understand the obstacles might encountered during BI system implementation. After conducted a detailed evaluation, some of these barriers can be included into the risks may encountered during implementation. This will increase the comprehensive of proposal for BI adoption and comprise a 360° overview to management.

Throughout this research study, executives are competent to be aware of the implementation trends of IT application and extended to BI system. An assessment on the trends and implication to existing business and operation can be further carried out by the executives. This can be an extra persuasive point for BI adoption in a corporate.

With the high exposure of BI system among corporate, the changes of implementing BI widely accepted will be increased. Consequently, the failure rate also might respectively decreases when the environment readiness and barriers had been analysed comprehensive.

5.5 Limitations and Recommendations

In Malaysia, the research studies conducted were facing a common limitation which is small sample size. The respondents based on small sample size will be less accurate and do not represent the defined population. In this research, a total of sixty eight (68) respondents was collected which is respectively a small sample size. This sample size was unable to represent the whole population of employees in Malaysia's enterprises who uses the BI applications in their daily jobs.

The small sample size also limits the analysis techniques applied to the data collected. The multivariate analysis techniques such as factor analysis requires a large sample size to produce an accurate result. In this study, the regression and one-way ANOVA were chosen by considering the sample size.

Unwillingness to share the information among the Malaysia corporate also caused the difficulties of collecting sufficient samples and information related to research conducted. The corporate research is still less accepted in Malaysia due to lack of confidence on the privacy applied to the information sharing. Possibility to allow competitors access to the information sharing is a serious concern raised by business owners.

This research study was limited to a general population associated with BI adoption due to resources constraints and limitation faced. Hence, the research study can be extended to a specific population in Malaysia and also conducting comparison. The following recommendation will be suggested for future research.

1. Extended the research by comparing the corporate has adopted BI system against the corporate is not implemented BI system. The significant drivers and barriers might have difference between these two populations. This will give the executives broader views on the BI adoption.

2. Extended the research by comparing the results between SMEs against large corporate. The drivers and barriers encountered might various when the corporate is more affordable on BI investment as well as greater environment readiness against another population. By analyse the corporate conditions in the research study; the results provided will be more accurate and specific.

3. Extended the research by conducting an empirical research based on case study. In-deep observation can be conducted throughout a direct interaction with the target respondent. This qualitative research will provide a real-world case study to the executives as an extension of general survey.

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APPENDIX A: SURVEY QUESTIONNAIRE

UNIVERSITI TUNKU ABDUL RAHMAN
INSTITUTE OF POSTGRADUATE STUDIES AND RESEARCH

QUESTIONNAIRE

DRIVERS AND BARRIERS TO BUSINESS INTELLIGNECE (BI)

ADOPTION IN MALAYSIA

February 2011

Universiti Tunku Abdul Rahman
13, Jalan 13/6, 46200 Petaling Jaya,
Selangor Darul Ehsan, Malaysia
http://www.utar.edu.my

Dear Respondent,

I am a student of Master of Business Administration (MBA) at Universiti Tunku Abdul Rahman (UTAR). In order to complete my master, I am conducting a study of **Drivers & Barriers to Business Intelligence (BI) Adoption in Malaysia** for my research project. The objective of this research project is to understand reasons of company implement BI and obstacles that stopping company to do so. Throughout your participation, I eventually hope to find out which drivers and barriers are significantly influence the BI implementation in companies.

Enclosed with this letter is a brief questionnaire to ask about drivers & barriers to adopt BI in your company. Besides personal & company profile, you only required to select answer from Strongly Disagree to Strongly Agree against the given statements. It estimated to take only 15 - 20 minutes to complete this questionnaire. All your answers will only use for my research analysis and all personal particulars will not disclose to anyone else.

If you need any clarification on this research, you shall contact me via email of fongyee1208@gmail.com or supervisor of my research project, Mr. Hen Kai Wah (UTAR lecturer) via email of henkw@utar.edu.my.

Thank you.

Sincerely,
Loo Fong Yee
Student ID: 07UKM03086
UTAR MBA Student

(A) **Personal Profile**

Please fill up your personal particulars for demographic analysis.

Gender:
- ☐ Male
- ☐ Female

Age:
- ☐ 21 - 30
- ☐ 31- 40
- ☐ 41-50
- ☐ 51 & above

Position:
- ☐ CIO
- ☐ IT Manager
- ☐ Director Board
- ☐ VP / Regional Head
- ☐ Business Management / Middle Management
- ☐ Junior Executive / Officer
- ☐ Others __________

User type for BI:
- ☐ IT staff
- ☐ Executive user
- ☐ Occasional Information User
- ☐ Extranet, Partner, Consumers
- ☐ Functional Managers
- ☐ Power User, Business Analyst (BI)
- ☐ Others ___________

(B) **Company Information**

Please fill up company information below for geographical analysis.

IT- Business Initiatives:
(May tick more than 1)
- ☐ Business process improvement
- ☐ Reducing enterprise cost
- ☐ Improving enterprise workforce
- ☐ Targeting customers and markets more effectively
- ☐ Expanding current customer relationships
- ☐ Attracting and retaining new customers
- ☐ Increasing the use of information
- ☐ Creating new products or services
- ☐ Managing change initiatives
- ☐ Expanding into new markets and geographies

Company Industry:
- ☐ Banking
- ☐ Telecommunication
- ☐ Information Technology
- ☐ Government
- ☐ Health care
- ☐ Others _______

Annual IT Budget:
(in MYR)
- ☐ 0-200,00
- ☐ 201,000-500,000
- ☐ 501,000 – 1 million
- ☐ 1 – 5 million
- ☐ Above 5 million

(C) **Company - BI Adoption Level**

Please select yes if your company has adopted the following BI modules and select adoption level.

1. **Reporting** – create and generate weekly, monthly or annual reports that required by department or management. ☐ Yes ☐ No
   If yes: ☐ Individual level ☐ Departmental level ☐ Corporate level

2. **Statistical Analysis** – perform data analysis to support corporate operation. ☐ Yes ☐ No
   If yes: ☐ Individual level ☐ Departmental level ☐ Corporate level

3. **Decision Making** – provide information in right format to assist in decision making. ☐ Yes ☐ No
   If yes: ☐ Individual level ☐ Departmental level ☐ Corporate level

4. **Forecasting –** use historical data and pre-defined algorithm to forecast future business ☐ Yes ☐ No
   If yes: ☐ Individual level ☐ Departmental level ☐ Corporate level

5. **KPI** – pre-defined KPI measurement and provide employee or department KPI for assessment purpose. ☐ Yes ☐ No
   If yes: ☐ Individual level ☐ Departmental level ☐ Corporate level

(D) **Drivers to Business Intelligence Adoption**

Please select from range of 1 to 5 representing Strongly Disagree to Strongly Agree.

No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	Reduce information analysis cost	1	2	3	4	5
2	Desire to increase business competitiveness	1	2	3	4	5
3	Desire to increase profitability	1	2	3	4	5
4	Enterprise wide data driven decision making capability	1	2	3	4	5
5	Availability of data analysis tool	1	2	3	4	5

No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
6	Risk mitigation (Financial or Operational)	1	2	3	4	5
7	Rich reporting capability	1	2	3	4	5
8	Optimization in resource allocation	1	2	3	4	5
9	Deeper data insight	1	2	3	4	5
10	Organisational efficiency (Financial or Operational)	1	2	3	4	5
11	Vendor website role in BI buying decision	1	2	3	4	5
12	Rapid change in data volumes lead to a need for BI	1	2	3	4	5
13	Governance requirements (IT & Corporate)	1	2	3	4	5
14	Stakeholder demands	1	2	3	4	5
15	Expanding ERP (Enterprise Resource Planning)	1	2	3	4	5
16	Data availability readiness	1	2	3	4	5
17	‘Forward-looking view’: Forecasting	1	2	3	4	5
18	Align with corporate strategy	1	2	3	4	5
19	Effective decision making at all	1	2	3	4	5

No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
	levels of company					
20	Predict market trends	1	2	3	4	5
21	Improve enterprise performance	1	2	3	4	5
22	Single version of truth	1	2	3	4	5
23	Current and accurate information	1	2	3	4	5
24	Rapidly change of information needs	1	2	3	4	5
25	Customer service excellence	1	2	3	4	5
26	More efficient service	1	2	3	4	5
27	Increase service costs	1	2	3	4	5
28	Better and faster decisions	1	2	3	4	5

(E) <u>Barriers to Business Intelligence Adoption</u>

Please select from range of 1 to 5 representing Strongly Disagree to Strongly Agree.

No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	Upfront costs	1	2	3	4	5
2	Setup costs	1	2	3	4	5
3	Running costs	1	2	3	4	5

No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
4	Lack of skills to implement BI/Data Warehouse	1	2	3	4	5
5	Lack of executive board interest	1	2	3	4	5
6	No real or tangible benefits	1	2	3	4	5
7	Poor Return of Investment (ROI)	1	2	3	4	5
8	Lack of knowledge about BI products	1	2	3	4	5
9	Lack of technology (pre-BI infrastructure)	1	2	3	4	5
10	Data security concerns (Pervasive BI and Outsourced version)	1	2	3	4	5
11	Insufficient government support for BI initiatives	1	2	3	4	5
12	Lack of a complete BI Suite offering by any vendor	1	2	3	4	5
13	Typical BI systems not optimized for OLTP[1]	1	2	3	4	5
14	Frequent data latency issues	1	2	3	4	5
15	Implementation time lags	1	2	3	4	5
16	BI project complexity	1	2	3	4	5

No.	Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
17	High costs of OLAP[2] based systems (BI tuned)	1	2	3	4	5
18	BI tools highly specialized for wide spread use	1	2	3	4	5
19	Complexities of data management	1	2	3	4	5
20	Fragmented data sources in the enterprise	1	2	3	4	5

Note:

[1] <u>On-line Transaction Processing (OLTP):</u> Refers to a class of systems that facilitate and manage transaction-oriented applications, typically for data entry and retrieval transaction processing. OLTP has also been used to refer to processing in which the systems respond immediately to user requests. An automatic teller machine (ATM) is an example of a commercial transaction processing application. The technology is used in many industries, including banking, airlines, mail-order, supermarkets, and manufacturing. Applications including electronic banking, order processing, employee time clock systems, e-commerce, and e-Trading.
(Source: Transaction Processing Performance Council Website, http://www.tpc.org, accessed Dec, 2010.)

[2] <u>On-line Analytical Processing (OLAP):</u> OLAP is part of the broader category of business intelligence, which also encompasses relational reporting and data mining. The typical application of OLAP are in business reporting for sales, marketing, management reporting, business process management (BPM), budgeting and forecasting, financial reporting etc.
(Source: Online Transaction Processing Council website, http://www.syncorp.com , accessed Dec, 2010.)

- End of Survey-