AN EMPIRICAL STUDY ON BUSINESS INTELLIGENCE ADOPTION AND MATURITY IN MALAYSIAN ORGANIZATIONS

By

ONG IN LIH

A dissertation submitted to the
Department of Internet Engineering and Computer Science,
Faculty of Engineering and Science,
Universiti Tunku Abdul Rahman,
in partial fulfillment of the requirements for the degree of
Master of Computer Science
October 2014

ABSTRACT

AN EMPIRICAL STUDY ON BUSINESS INTELLIGENCE ADOPTION AND MATURITY IN MALAYSIAN ORGANIZATIONS

Ong In Lih

Business intelligence (BI) is a strategic resource that helps organizations to facilitate decision making processes. Despite the apparent significance of BI, many organizations are still in the early stage of BI implementation. The primary aim of this research is to study the BI maturity level in Malaysian organizations, and factors that affect the BI maturity. This maturity model comprises of four dimensions: organizational management, process, technology and outcome, spanning across five levels of maturity. For each dimension, it spells out criteria to move from the lowest maturity level to the highest maturity level. An empirical research was undertaken using a structured questionnaire approach to test the BI maturity model. The findings showed that no organizations have achieved level 5 and 52 percent of them are still at moderate level of BI maturity across all the four dimensions of the maturity model. This implies that most organizations have yet enjoyed the full benefits from their BI investments. The findings also revealed that most organizations had achieved the highest BI maturity level in technology and outcome dimensions, followed by organizational management and process dimensions. There are still rooms for improvements where organizations can and should move up the maturity hierarchy so that they can gauge more

potential BI benefits such as streamline operations and improve profitability. Besides, the results obtained from the hypotheses testing showed that demographic variables such as organizational size and age of BI initiatives did not have significant effects on the BI maturity, except industry type. The results also indicated that organizations from service industries achieved higher mean score than non-service industries. Overall, all the research objectives have been achieved. It is believed that this BI maturity model is comprehensive enough to cover all dimensions of consideration when an organization plans to implement or expand BI.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest appreciation and sincere gratitude to my supervisor, Dr. Siew Pei Hwa for her invaluable guidance, advice, and motivation from the beginning to the end for this research.

Dr. Siew has been an excellent supervisor and has inspired me greatly to work in this research. Her willingness and patience to guide me contributed tremendously to the success of my research. I also would like to thank her for sharing me lots of useful references and suggestions that related to the topic of my research.

I would like to send my gratitude to my co-supervisors, Dr. Wong Siew Fan (currently attached to Sunway University) and Dr. Khor Siak Wang for their guidance and advice. Dr. Wong provided lots of helpful information and ideas throughout the publication of conference and journal papers.

I would like to take this opportunity to thank all the respondents from Malaysian organizations who participated in the survey. Their kind assistance and contributions are deeply appreciated. Without cooperation from them during the data collection, I would not be able to complete this research seamlessly.

An honourable mention goes to my family members for their understandings, encouragement, and moral supports on me in completing this research. Without their help, I may encounter many difficulties while doing this research.

Without all the above-mentioned people, this research would have not started or finished. Many thanks must be given to them for giving me this opportunity and invaluable experiences throughout this Master degree course.

APPROVAL SHEET

This dissertation entitled "**AN EMPIRICAL STUDY ON BUSINESS INTELLIGENCE ADOPTION AND MATURITY IN MALAYSIAN ORGANIZATIONS**" was prepared by ONG IN LIH and submitted as partial fulfillment of the requirements for the degree of Master of Computer Science at Universiti Tunku Abdul Rahman.

Approved by:

____
(Asst. Prof. Dr. SIEW PEI HWA) Date: 7th October 2014
Assistant Professor/Supervisor
Department of Multimedia Design & Animation
Faculty of Creative Industries
Universiti Tunku Abdul Rahman

____
(Asst. Prof. Dr. KHOR SIAK WANG) Date: 7th October 2014
Assistant Professor/Co-Supervisor
Department of Information Systems
Faculty of Information and Communication Technology
Universiti Tunku Abdul Rahman

FACULTY OF ENGINEERING AND SCIENCE

UNIVERSITI TUNKU ABDUL RAHMAN

Date: 7th October 2014

SUBMISSION OF DISSERTATION

It is hereby certified that **Ong In Lih** (ID No: **11UEM01659**) has completed this dissertation entitled "AN EMPIRICAL STUDY ON BUSINESS INTELLIGENCE ADOPTION AND MATURITY IN MALAYSIAN ORGANIZATIONS" under the supervision of Dr. Siew Pei Hwa (Supervisor) from the Department of Multimedia Design & Animation, Faculty of Creative Industries, and Dr. Khor Siak Wang (Co-Supervisor) from the Department of Information Systems, Faculty of Information and Communication Technology.

I understand that University will upload softcopy of my dissertation in pdf format into UTAR Institutional Repository, which may be made accessible to UTAR community and public.

Yours truly,

____

(ONG IN LIH)

DECLARATION

I **ONG IN LIH** hereby declare that the dissertation is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

Name ONG IN LIH

Date 7th October 2014

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

BI	Business Intelligence
CMM	Capability Maturity Model
DSS	Decision Support Systems
DW	Data Warehousing
EIS	Executive Information Systems
ETL	Extract-Transform-Load
IS	Information Systems
MDM	Master Data Management
MIS	Management Information Systems
ODS	Operational Data Store
OLAP	Online Analytical Processing

CHAPTER 1

INTRODUCTION

1.1 Introduction

In recent years, market enthusiasm toward business intelligence (BI) is overwhelming (Evelson, 2012; Gartner, 2013). This is evident with increasing parades of BI vendors as well as raising number of organizations, especially large enterprises that either have adopted or are seriously considering implementing BI (Guarda et al., 2013). According to Gartner (2013), BI spending rose 16 percent in 2012 to hit $12.9 billion. Meanwhile, a recent CIO survey of 251 IT leaders revealed that more than 56 percent of organizations are considering expanding their usage of BI (IDG Enterprise, 2013). Such enthusiasm can be attributed to their recognition of the value of BI.

Dayal et al. (2009) define BI as “a collection of data warehousing, data mining, analytics, reporting and visualization technologies, tools, and practices to collect, integrate, cleanse, and mine enterprise information for decision making” (p. 1). Specifically, BI serves as a source of competitive advantage in enabling organizations to gain knowledge and insights that result in effective business actions and improved business performance (Gangadharan and Swami, 2004).

Even though organizations are becoming aware of the value of BI, many still have not gained full benefits from their investment (Heyns et al., 2009). The main reason is that many of them only adopt basic BI capabilities, and have not touched on the implementation of higher level analytics and intelligent functions (SAS, 2008). The term "maturity" is being used to describe such differences in the level of BI implementation. An organization that achieves the highest BI maturity level is supposed to have the most comprehensive BI functionalities and capabilities (Eckerson, 2007b). They will reap full benefits of BI. An organization that is at the lowest level of BI maturity level, however, only touches on very basic features of BI despite their humongous investment into the initiative.

In general, maturity is the "state of being fully grown or developed" (Hornby, 2010, p. 1077). For organizations to achieve a higher level of maturity in their BI initiatives, they have to first recognize their current position in the maturity hierarchy. Then, they have to know the elements that need to be improved in order to move up to the next maturity level. A review of the literature shows that there is a lack of academic research in providing systematic guidelines for this evolutionary transformation path. Thus, this research gives emphasis to the development and examination of a BI maturity model with the goal of eventually using the model to guide organizations in their effort to move toward a higher maturity level in their BI initiatives. It synthesizes different viewpoints of BI into a comprehensive model that takes into account critical dimensions, commonly mentioned in the literature. It also aims to study the effects of demographic variables (in terms of the types of industry, organizational size, and age of BI initiatives) on BI maturity in an organization.

1.2 Problem Statement

The implementation of BI initiative is a length and complex undertaking compared to other information technology initiatives, as it requires large amount of organizational resources and consistent improvement effort (Watson et al., 2004). There are some issues pertaining to the implementation of BI.

1.2.1 Current State of BI Maturity

Based on a web survey of 392 BI professionals conducted worldwide in June 2008, TDWI (2008) reported that only 28 percent of respondents described their BI implementation as being in advanced stages. According to Ventana Research's 2010 benchmark report of 308 individuals (involving executives, management, and users across a range of roles and titles working in IT organizations) which was also conducted worldwide, 85 percent responded that their organizations are still at the lower levels of a maturity chart in their use of BI due to poor usage of advanced BI capabilities (Ventana Research, 2010).

Even though organizations are becoming aware of the value of BI, many are not actively using it and are still relying heavily on ad hoc data collection and reporting tools such as Excel spreadsheets in their decision-making. More than 70 percent of respondents are still performing query against data sources and relying on spreadsheets to analyze data (Ventana Research, 2010). Extensive use of ad hoc tools may lead to problems such as lack of integrity, inconsistency, time consuming, inability to meet business requirements, and poor decision making (Davenport and Harris, 2007; Ventana Research, 2010).

1.2.2 Poor Understanding of BI Implementation and Its Values

BI has been one of the top technology priorities for many worldwide organizations (Luftman and Ben-Zvi, 2010). Despite the apparent significance of BI to the success of business activities, many organizations still have not successfully reaped full benefits from their BI investments such as cost savings and real time visibility into business operations. A survey of 3000 individuals (involving executives and business analysts) conducted in 2010 reported that 38 percent of respondents lack of understanding on how to use BI to improve their business (Wailgum, 2010). Often, cases of BI adoption mentioned in the press are those companies from developed countries such as USA, Australia, New Zealand, and Germany. There is a lack of reports of deployment in developing countries such as Malaysia. This lack of press coverage is doing a disservice to Malaysian companies, thus leading to a low usage and understanding of BI tools (Tan, 2007). For example, many are unaware of BI and the associated values. Even among those who are aware of BI, they may still be doubtful of the return on investment. As a result, the organizations are delaying their BI deployment or expansion that could have brought competitive edge to their business (Tan, 2007).

1.2.3 Uncertainty on the Path to Follow

Many organizations have recognized the importance of increasing commitment towards delivering long term success of BI. A successful BI implementation requires effective strategies and governance involving people with appropriate skills and supported by right tools and technologies. However, the roadmap for a successful BI implementation and progression towards a higher level is not clear (Hawking and Sellitto, 2010). Organizations cannot determine which path of organizational strategy to follow for further improvement and continuous business growth in the future. This may lead to problems such as inability to meet business requirements, ineffective decision making, and poor business performance. BI is not just a destination involving one-time and simple technology implementation, but is a journey that needs to continue to evolve over time to support changing business demands (Gangadharan and Swami, 2004; Gunter, 2007).

1.2.4 Shortcomings of Existing BI Maturity Models

Successful implementation of BI initiative requires large amount of organizational resources and consistent process improvement efforts. As such, numerous maturity models have emerged as a key instrument to provide a roadmap for organizations. However, much of the existing BI maturity models mainly focus on technical and process aspects. In fact, many organizations are still in the early stages of BI implementation due to lack of focus on other critical aspects (such as organizations) that require attention and improvement. For instance, lack of user training and business involvement in the process of BI implementation will lead to lower maturity level (Davenport, 2006). According to a 2010 survey of 3000 executives and business analysts, the obstacles in BI adoption are mainly in management and culture, instead of technology and data (Wailgum, 2010). Aside from that, there is limited literature available regarding the role of types of industry, organizational size, and age of BI initiatives play into the BI maturity.

Moreover, there is a lack of a comprehensive BI maturity model to assess and clarify organizations, particularly in Malaysia according to their BI maturity levels. The knowledge of the BI maturity level is essential in helping organizations formulating strategy to move up the ladder of maturity level and derive more potential benefits from BI.

1.3 Research Objectives and Hypotheses

Given the importance of assessing the maturity level in organizations to understand their BI capabilities for effectively planning, assessing, and managing BI initiatives (through identifying the problems about current state of BI implementation as discussed in previous section, and reviewing the extant literature about BI related topics which are discussed in chapter 2), the primary aim of this research is to study the BI maturity level in Malaysian organizations, and factors that affect the BI maturity. Its main objectives were derived from a principal research question: How can the BI maturity level in the Malaysian organizations be assessed?

From the principal research question, three more sub-research questions were derived as below:

i. **Sub-question 1:** What are the key dimensions and associated components to be built into each maturity level of a BI maturity model for assessing the maturity level of BI implementation in Malaysian organizations?

ii. **Sub-question 2:** What is the current maturity level of the BI implementation in Malaysian organizations?

iii. **Sub-question 3:** Do demographic variables such as types of industry, organizational size, and age of BI initiatives have significant effects on the BI maturity level in Malaysian organizations?

The main and sub-questions were further analyzed to provide the basis for the related objectives of this research.

1.3.1 Research Objectives

Three research objectives were formed to address the above research questions:

i. **Objective 1:** To develop and empirically test a multi-dimensional BI maturity model with distinct maturity levels and associated components that assesses the BI maturity level in Malaysian organizations.

ii. **Objective 2:** To assess the current maturity level of BI implementation in Malaysian organizations.

iii. **Objective 3:** To study the effect of demographic variables such as types of industry, organizational size, and age of BI initiatives on the level of BI maturity in Malaysian organizations.

1.3.2 Research Hypotheses

Based on the research objectives, the research was assuming that:

i. The proposed multi-dimensional BI maturity model with distinct maturity levels and associated components enables Malaysian organizations to assess their BI maturity level. Having this maturity model as guidance, organizations could effectively devise a systematic plan to expand their BI capabilities.

ii. Types of industry could affect the evolution of BI maturity.

iii. Due to large organizations (in terms of employees employed) usually have more resources and expertise available to deliver successful BI initiatives, they tend to have a higher level of BI maturity than smaller organizations.

iv. The longer the BI initiatives exist, the higher the BI maturity level becomes.

From the research assumptions ii through iv, the following hypotheses were formulated:

H1: The types of industry have significant effects on the BI maturity.

H2: The organizational size has a significant effect on the BI maturity.

H3: The age of BI initiatives has a significant effect on the BI maturity.

1.4 Significance of the Research

Despite an increased interest in BI, it is surprising that little empirical study has actually been conducted on BI maturity assessment. Therefore, the research findings could provide significant guidelines for organizations with a lower level of BI maturity and in the transitional to higher BI maturity. This research made two main contributions in terms of theoretical and practical perspectives.

From the theoretical perspective, this research contributed to the context understanding of BI maturity model as well as the key dimensions and associated factors deemed important by BI stakeholders. The development and evaluation of the proposed BI maturity model covers different viewpoints of BI and addresses the limitation of existing BI maturity models. Aside from that, the empirical results can shed some light on the various demographic variables that have significant influences on the evolution of BI maturity.

From the practical perspective, the BI maturity model serves as the fundamental framework for an organization to assess existing BI implementation and uncover the key weaknesses of BI in organizations. In addition, the maturity model also allows organizations to determine whether to optimize their usage of BI and to plan a systematic path for evolving into higher levels of maturity.

1.5 Research Scope

This research focuses on the development and evaluation of a multi-dimensional BI maturity model encompassing relevant dimensions and associated components for assessing the BI maturity level in Malaysian organizations. The research flow is depicted in Figure 1.1.

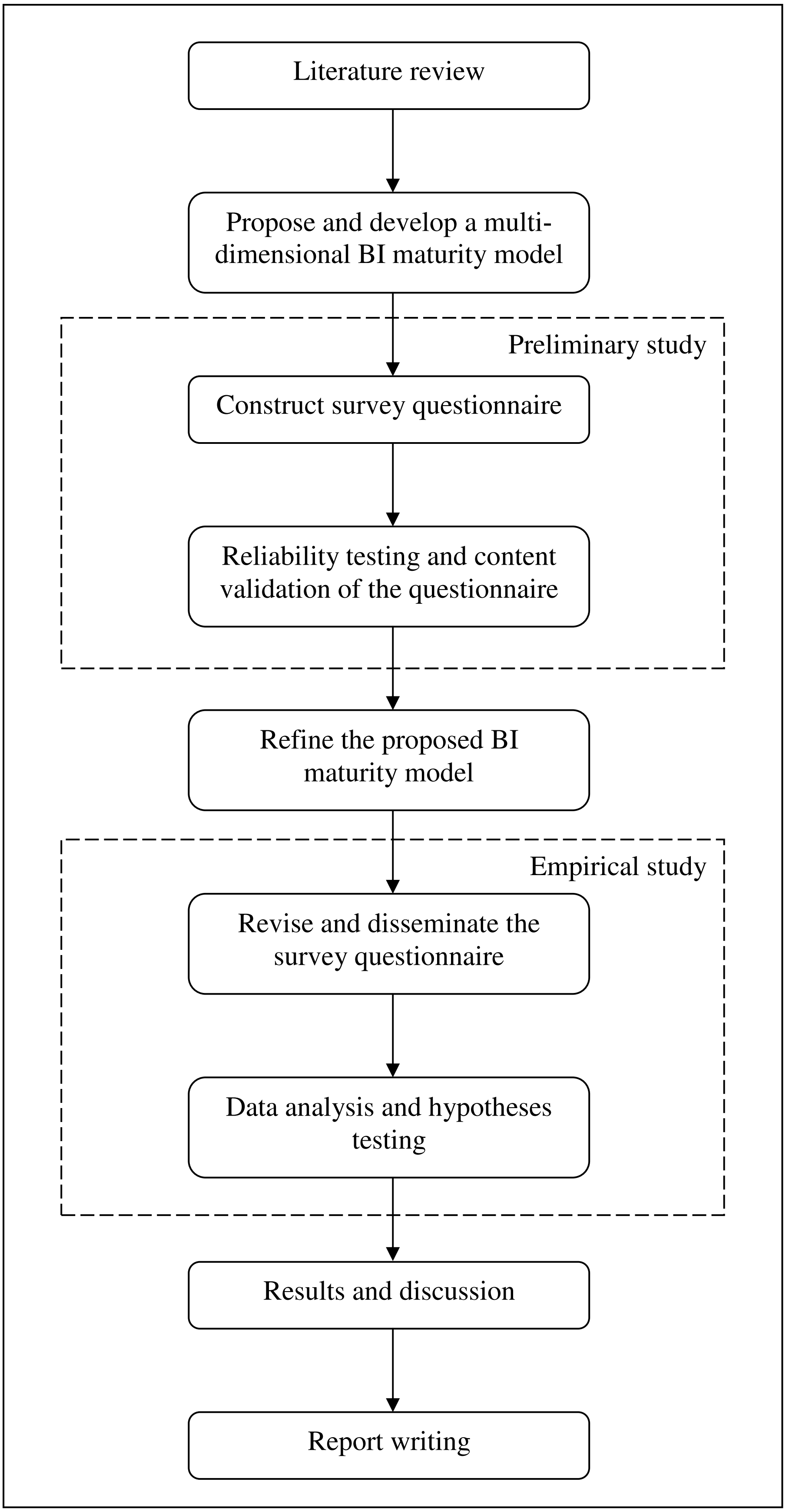


Figure 1.1: Research flow

This research does not attempt to shape or transform current industry practices, rather it aims to identify and understand the key dimensions that affect the BI maturity. The scope of the research encompasses tasks and deliverables as follows:

i. The development of a multi-dimensional BI maturity model called MOBI (Malaysian Organizations' Business Intelligence) maturity model comprising of four dimensions (i.e. organizational management, process, technology, and outcome), which is further described in section 2.7,

ii. The assessment of BI maturity in Malaysian organizations, which is further described in chapter 4, and

iii. The analysis on the effects of organizations' demographic variables (i.e. types of industry, organizational size, and age of BI initiatives) on BI maturity in Malaysia, which is further described in chapter 4.

In particular, the early essential step before the creation of maturity model is to critically review the existing research literature. Following the literature review, specific research questions are identified, accompanied by a set of research objectives and hypotheses. The structured questionnaire survey approach was used to evaluate the BI maturity model and validate research objectives. A preliminary investigation is conducted to ensure the quality of survey instrument before the empirical study is undertaken. As such, reliability of the scale is tested and content is validated, subsequently leading to the refinement of the model. The questionnaire is then revised and disseminate to research samples spanning across various industries. In line with the research scope, the survey targets the middle and senior management with BI responsibilities in the selected Malaysian organizations across a wide range of organizational size.

Data collected from samples were described using various descriptive procedures, frequency tables, and different types of charts (e.g. pie and bar charts). Statistical methods such as descriptive analysis, independent-sample t-test, One-way ANOVA (analysis of variance) were then used to test the hypotheses. Following that, the analyzed data are examined and interpreted to draw out wider implications of the findings. The final step in the research flow is writing a report about the research and results.

1.6 Summary

BI has become a strategic resource which can help organizations to facilitate improved decision making processes and to sustain competitive advantages. In particular, there are many organizations wish to move toward a higher level of maturity in their BI implementation. In response to this, this research develops and tests a comprehensive BI maturity model encompassing key dimensions and associated components for managing BI initiatives. This research also aims to research on how effective is the proposed BI maturity model in measuring the maturity of an organization's BI implementation. It is believed that the proposed BI maturity model has great potential in providing an effective guideline for Malaysian organizations to plan their evolutions systematically and achieve further improvement.

1.7 Dissertation Structure

Chapter 2 covers the review of literatures related to several topics which lays the theoretical foundation for this research. First, it provides an overview of the concept of BI and its evolution. Second, it illustrates and discusses different views of BI, followed by the concept of maturity model and a review of the existing BI maturity models. Third, it describes the proposed BI maturity model.

Chapter 3 describes the research methods employed in this research. Then, it discusses the results of a pilot study. Chapter 4 focuses on the discussion of the results of data analysis and hypotheses testing.

Chapter 5 covers several topics to wrap up the findings and discussions of the research. It encompasses research contributions as well as the limitations and recommendations of the research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

It is necessary to conduct an extensive literature review pertaining to the research area in order to develop a better understanding and insight into the topics discussed. Reviewing the existing literature critically will provide a solid theoretical foundation to the selection of research methodology, as well as justification that the proposed research contributes to the body of knowledge (Levy and Ellis, 2006). This chapter discusses the following topics:

- Definition of business intelligence
- Evolution of business intelligence
- Business intelligence cycle
- Business intelligence tools
- Business intelligence maturity models
- Proposed business intelligence maturity model
- Related work on the influence of demographic variables on the BI maturity level

2.2 Definition of Business Intelligence

The term “business intelligence” was first used by Hans Peter Luhn in 1958 in an IBM journal article. According to Luhn (1958), BI is defined as:

> Business is a collection of activities carried on for whatever purpose, be it science, technology, commerce, industry, law, government, defense, et cetera. The communication facility serving the conduct of a business (in the broad sense) may be referred to as an intelligence system. The notion of intelligence is also defined here, in a more general sense, as “the ability to apprehend the interrelationships of presented facts in such a way as to guide action towards a desired goal” (p. 314).

However, BI became widely recognized in the 1990s only after BI was used by Howard Dresner, a research analyst of Gartner Group in 1989 (Shollo and Kautz, 2010). According to Power (2002), Howard Dresner explained BI as “a set of concepts and methods to improve business decision making by using fact-based support systems” (p. 128). BI is also described as a process of collecting, analyzing and transforming data into relevant information, and then processing it into knowledge to improve business performance (Azvine et al., 2006; Sallam et al., 2010).

Even though there has been a growing interest in BI area, there is no commonly accepted definition of BI (Pirttimäki, 2007; Wixom and Watson, 2010). The literature shows that the definition of BI has evolved from a one-dimensional view to a multi-dimensional view (Vitt et al., 2010). In view of this, Table 2.1 presents a number of BI definitions from various sources. These definitions provide a general understanding of the BI concept and show clearly why BI is so popular among a large group of modern organizations.

Table 2.1: Definitions of business intelligence

Definition	Source
"All about how to capture, access, understand, analyse and turn one of the most valuable assets of an enterprise – raw data – into actionable information in order to improve business performance."	Azvine et al. (2006, p. 215)
"A collection of data warehousing, data mining, analytics, reporting and visualization technologies, tools, and practices to collect, integrate, cleanse, and mine enterprise information for decision making."	Dayal et al. (2009, p. 1)
"A business function with clear goals and a mission: to collect, analyze, evaluate, and disseminate relevant business intelligence information, metrics and status, for assisting leaders and managers in making informed decisions that change behaviors and move the business toward meeting goals, objectives and strategy."	DeGeneres (2008, p. 1)
"The ability of an enterprise to act effectively through the exploitation of its human and information resources."	English (2005, p. 2)
"The result of in-depth analysis of detailed business data, including database and application technologies, as well as analysis practices."	Gangadharan and Swamy (2004, p. 140)
"The process of turning data into information and then into knowledge."	Golfarelli et al. (2004, p. 1)
"A process of taking large amounts of data, analyzing that data, and presenting a high-level set of reports that condense the essence of that data into the basis of business actions, enabling management to gain new insights and thereby contributing to their business decisions."	Gottschalk and Solli-Saether (2010, p. 43)
"Knowledge about your customers, your competitors, your business partners, your competitive environment, and your internal operations - that gives you the ability to make effective, important, and often strategic business decisions."	Haag et al. (2007, p. 124)
"The delivery of accurate, useful information to the appropriate decision makers within the necessary timeframe to support effective decision making."	Larson (2012, p. 11)
"(1) Relevant information and knowledge describing the business environment, the organization itself, and its situation in relation to its markets, customers, competitors, and economic issues; (2) An organized and systematic process by which organizations acquire, analyze, and disseminate information from both internal and external information sources significant for their business activities and for decision making."	Lönnqvist and Pirttimäki (2006, p. 32)

Table 2.1 (Continued)

Definition	Source
"A discipline of developing information that is conclusive, fact-based, and actionable. Business intelligence gives enterprises the ability to discover and utilize information they already own, and turn it into the knowledge that directly affects corporate performance."	Pareek (2007, p.1)
"The conscious, methodical transformation of data from any and all data sources into new forms to provide information that is business-driven and results-oriented. It will often encompass a mixture of tools, databases, and vendors in order to deliver an infrastructure that not only will deliver the initial solution, but also will incorporate the ability to change with the business and current marketplace."	Ranjan (2008, p. 461)
"A range of methodologies, technologies, skills, competencies, and applications businesses implement and utilize in order to better understand their commercial context."	Riley and Delic (2010, p. 446)
"Providing decision makers with valuable information and knowledge by leveraging a variety of sources of data as well as structured and unstructured information."	Sabherwal and Becerra-Fernandez (2009, p. 6)
"A set of business information processes for collecting and analyzing enterprise (business) information, the technology used in these processes, and the information (knowledge) obtained from these processes."	Shariat and Hightower (2007, p. 42)
"Business information and business analyses within the context of key business processes that lead to decisions and actions and that result in improved business performance."	Williams and Williams (2007, p. 2)
"A broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users to make better decisions."	Wixom and Watson (2010, p. 14)
"From a data analysis perspective, business intelligence is the process of gathering high-quality and meaningful information about the subject matter being researched that will help the individual(s) analyzing the information draw conclusions or make assumptions. From an information systems perspective, business intelligence is the system that provides users with online analytical processing (OLAP) or data analysis to answer business questions and identify significant trends or patterns in the information that is being examined."	Wu (2000, p. 1)

Drawing upon extant literature, it was found that the scope and definition of BI have been extended to include product. As noted in the study of Jourdan et al. (2008), BI is viewed as both a process and a product. Petrini and Pozzebon (2009) provided a similar distinction of perspectives to BI in terms of technical and managerial perspectives. Shariat and Hightower (2007) characterized BI as a composition of process, technology, and product. Based on the definitions as presented in Table 2.1, four main focus of BI were identified for this research, namely organizational management, process, technology, and outcome as summarised in Table 2.2.

Table 2.2: Four main focus of BI

BI Focus	Description
Organizational management	The focus of BI is related to how an organization is structured to support the business processes and ensure long term success of BI implementation, such as having strong support from management and obtaining sponsorship to secure the necessary funding. It is also essential for an organization to have clear vision statement, understand the goals to be achieved, and define strategy for BI implementation.
Process	BI can be viewed as a process which consists of methods for organizations to generate useful information or intelligence (Jourdan et al., 2008; Petrini and Pozzebon, 2009). Large amounts of data collected from different internal and external sources are integrated, analyzed and transformed into information so that users at all levels are able to support decision making process and take actions, thereby improve business performance.
Technology	BI can be described as the usage of architectures, tools, applications, and technologies in facilitating various BI processes such as collecting, storing, analysing, and providing access to data to enable users make effective decisions in support of organizational perspective.
Outcome	BI is considered as the product or result of performing BI-related processes such as analyzing business data (e.g. information, knowledge, insights) which are useful to organizations for their business activities and decision making.

As can be perceived through Table 2.2, BI is a multi-dimensional term in which it can be defined in many ways from different perspectives. However, most of the sources tend to focus only on one or two dimensions. For instance, while the definition of English (2005) focused on one dimension (i.e. organizational management), the definitions of Dayal et al. (2009) and Ranjan (2008) spanned across both process and technology dimensions. In order to have a full understanding of BI concept in this research, it is vital to incorporate all the four dimensions as depicted in Table 2.3.

Table 2.3: Mapping the BI definitions based on four focus of BI

Dimension	Definition	Sources
Organizational management	Focus on how an organization is structured to support BI related business processes	English (2005); DeGeneres (2008); Riley and Delic (2010)
Process	Measure the extent to which activities of coordinating and managing BI environment are being carried out successfully	Wu (2000); Golfarelli et al. (2004); Azvine et al. (2006); Lönnqvist and Pirttimäki (2006); Shariat and Hightower (2007); DeGeneres (2008); Ranjan (2008); Dayal et al. (2009); Sabherwal and Becerra-Fernandez (2009); Gottschalk and Solli-Saether (2010); Riley and Delic (2010); Wixom and Watson (2010); Larson (2012)
Technology	Focus on the development and implementation of different architectures, tools, technologies, and applications to facilitate the process of producing the BI output	Wu (2000); Shariat and Hightower (2007); Ranjan (2008); Dayal et al. (2009); Riley and Delic (2010); Wixom and Watson (2010)

Table 2.3 (Continued)

Dimension	Definition	Sources
Outcome	Measure the results of implementing different BI components (e.g. people, processes, tools and architectures)	Wu (2000); Gangadharan and Swamy (2004); Azvine et al. (2006); Lönnqvist and Pirttimäki (2006); Haag et al. (2007); Pareek (2007); Shariat and Hightower (2007); Williams and Williams (2007); DeGeneres (2008); Larson (2012)

In regard to the research question, the four dimensions as revealed in Table 2.3 form the basis for the development of the proposed BI maturity model, which is discussed in section 2.7. The BI maturity model is then used as a diagnostic tool to determine an organization's current state of BI. Subsequently, the organizations could balance their BI resources and narrow their focus on possible areas they can improve it.

2.3 Evolution of Business Intelligence

BI system is a form of data-driven DSS that shared some of the objectives and tools of DSS and EIS systems (Negash and Gray, 2003). Specifically, it assists decision makers to "support business needs that are data intensive, have cross-functional focus, require a process view, and require advanced analytical methods" (Glancy and Yadav, 2011, p. 48).

From a historical standpoint, the underlying concept of BI is not new and it has been existed over the last 50 years in the area of information systems (IS) discipline. According to Wixom et al. (2011), the origins of BI can be traced back to the early 1970s when decision support systems (DSS) first introduced. Over the years, numerous applications such as executive information systems (EIS), online analytical processing (OLAP), data mining, predictive analytics, and dashboards have emerged and added to the domain of decision support applications (Watson and Wixom, 2007). Figure 2.1 summarizes some major development in the evolution of DSS concepts.

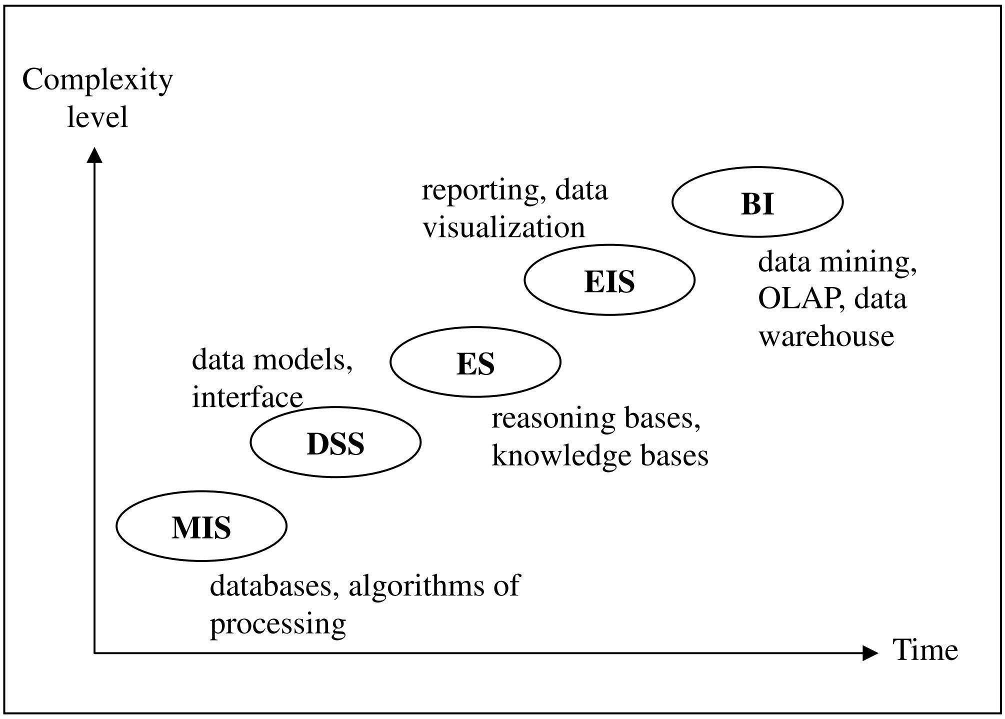


Figure 2.1: The evolution of DSS concepts

Source: Olszak and Ziemba (2007, p. 136)

In the early 1960s, management information systems (MIS) were developed to extract data from transaction processing systems (e.g. order entry, inventory control, and billing) and produce information for planning, control, and decision making (Arnott and Pervan, 2005).

In 1971, Gorry and Scott-Morton suggested the concept of DSS to address the shortcoming of MIS, i.e. mainly focus on structured decisions (Power, 2007). DSS were the first computerized information systems designed to utilize data and models to support semi-structured or unstructured decisions within organizations (Arnott and Pervan, 2005; Turban et al., 2011a). There are five specific types of DSS which are document-driven DSS, communication-driven DSS, data-driven DSS, model-driven DSS, and knowledge-driven DSS (Power, 2007). Data-driven DSS are the most common types of DSS that focus on managing large amount of internal historical data, real time operational data, and external data (Turban and Aronson, 2001).

In the 1970s and early 1980s, initial analytical software packages and spreadsheet software (e.g. Excel) was released in the marketplace (Petrini and Pozzebon, 2009). In the middle 1980s and early 1990s, the concept of EIS were introduced for senior executives to easily access to internal and external information through graphical user interface (e.g. dashboards) to support decision making (Shi et al., 2007; Rasmussen et al., 2009). EIS are a form of data-driven DSS and its architecture contains three different levels (Lungu and Bara, 2005):

- **Data management**: represented by relational database, data warehouses and other type of data resources,

- **Model management**: extracts, transforms and processes data, and
- **Data visualization tools**: provides a visual drill-down capacity that can assist managers examine data graphically and identify complex interrelationships.

However, the use of these systems have continually dropped in practice due to the fact that DSS were relatively limited in scope (for personal or small group use) and EIS was inflexible requiring many manual works to integrate data from disparate data sources (Shim et al., 2002; Frolick and Ariyachandra, 2006; Petrini and Pozzebon, 2009). In the early 1990s, these systems have been replaced and extended by BI systems such as data warehouse technologies, ETL (extract, transform, load) tools, and end user analytical software with OLAP capabilities (Watson and Wixom, 2007; Petrini and Pozzebon, 2009).

Figure 2.2 illustrates the evolution of a BI system and the various tools and techniques that maybe included in enhancing the capabilities of a BI system (Turban et al., 2011b).

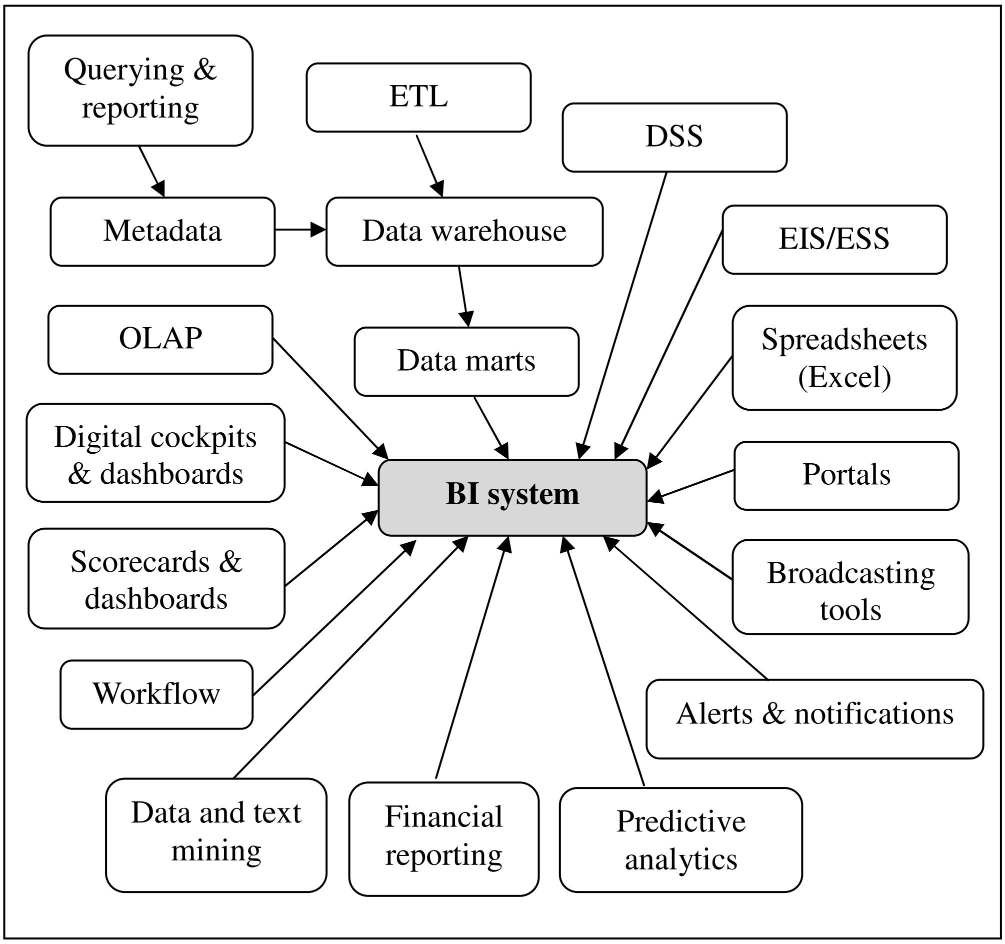


Figure 2.2: The evolution of a BI system

Source: Turban et al. (2011b, p. 19)

Today's BI users cover a wider range, typically including diversified stakeholders, front-line users, managers, and analysts (Turban et al., 2011a). Table 2.4 illustrates six major types of BI users with different BI tools and functions at varying levels of strategic importance. It is important to match user types with appropriate BI functionalities in order to maximize value for the organizations.

Table 2.4: Six major types of BI users

Types of Users	Number of Users	BI Tools and Functions	Strategic Value
IT	Few	• Developer • Administrator • Metadata • Security • Data management	Low
Power Users	Dozens	• Ad hoc query • OLAP • Reports • Data mining • Advanced analysis	High
Executives	Dozens	• Dashboard • Scorecard • Reports • CPM (corporate performance management)	High
Functional Managers	Dozens to hundreds	• Reports • Spreadsheet • OLAP view • BAM (business activity monitoring) • CPM	Medium
Occasional Information Consumers	Hundreds to thousands	• Reports • Spreadsheet	Low
Extranet: Partners, Customers	Hundreds to thousands	• Reports	High

Source: Gartner (2004); Turban et al. (2011a)

2.4 Business Intelligence Cycle

Vitt et al. (2010) described BI as an ongoing cycle of processes where organizations set their goals, analyze the progress, uncover insight, take action, measure their success, and start the cycle again. In other words, there is a systematic or cyclical path that is composed of four phases describing the evolution of BI cycle: analysis, insight, action, and measurement as shown in Figure 2.3.

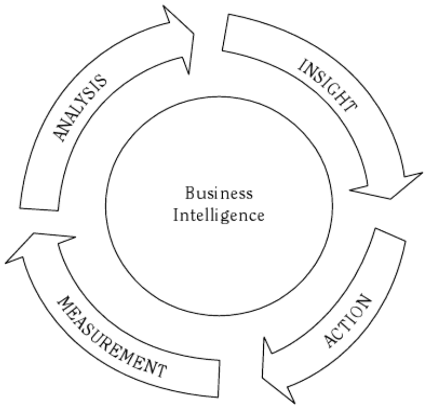


Figure 2.3: Evolution of BI cycle

Source: Vitt et al. (2010, p. 17)

As revealed in Figure 2.3, the process starts with gathering and transforming data collected from various sources into information through analysis. Next, information leads to insights and suggestions that enable organizations to take appropriate corrective actions. The result of actions taken can then be measured to identify which action is working well in the organizations. Finally, these measurements lead to new data for analysis and the BI cycle starts all over again.

2.5 Business Intelligence Tools

Different BI tools have emerged over time to assist organizations to deal with their specific problems and achieve desired outcomes. Generally, BI tools are used for "enabling organizations to understand their internal and external environment through the systematic acquisition, collation, analysis, interpretation and exploitation of information" (Chung et al., 2003, p. 1).

There are a variety of BI vendors in the market such as IBM Cognos, SAP BusinessObjects, Oracle, SAS, Information Builders, Microsoft, and MicroStrategy. These vendors provide BI products either as stand-alone BI tools or as integrated suites of BI applications. Each vendor offers different products that specialize in different BI capabilities. For instance, Oracle focuses on enterprise reporting, SAP BusinessObjects targets reporting and ad hoc query, and SAS concentrates on statistical analysis. While specialized capabilities are meant to bring out the uniqueness of each product, there are some common BI capabilities that are shared by all BI products. Examples of these capabilities include reporting, OLAP, and dashboard.

The scale of BI tools adoption in each organization can differ greatly depending on the business problems and user requirements (Dresner, 2010). For instance, organizations can adopt various types of BI tools from single or multiple vendors to meet their needs. However, there is no one BI tool that is best-suited or "one size fits all" to meet the divergent needs of everyone.

Table 2.5 shows some examples of Malaysian companies that have adopted BI along with descriptions of their usage type and the benefits gained. These examples were obtained through extensive online search using keywords of "Malaysia companies" and "BI tools". Additional search was also conducted by visiting vendor websites to collect published information on Malaysian companies that have adopted particular BI tools. Press releases and company websites were then checked to obtain information related to companies' BI usage and the benefits gained as a result of using the tools.

As evident from the Table 2.5, the adoption is not limited to one particular industry. Rather, wide varieties of industries in Malaysia have already started to deploy BI. Examples of these industries are banking and finance, communications, education, government, insurance, manufacturing, retail, healthcare, and service. However, the adoption is still restricted to large organizations with large data volume, due to the cost of deploying and managing BI systems is relatively high for small organizations. According to TDWI's research (Eckerson, 2004), it is found that the implementation cost of operational BI systems is generally about $1.1 million. Evelson (2010) also reported that the average cost of BI software for a department is $150,000. This price may be a burden for small-and-medium sized companies.

The usage of BI also varies by industrial needs. Due to specific requirements of niche industries, different BI tools are available to meet specific business needs.

Table 2.5: Examples of BI adoption in various industries in Malaysia

Industry	Company	Descriptions of BI Usage	Source
Banking and Finance	Bank Kerjasama Rakyat Malaysia Berhad (Bank Rakyat)	• MicroStrategy's BI Platform is implemented to provide strategic information for decision making and planning. • Employees can track product revenue and perform customer profitability analysis through the use of web-based analytical reporting solution.	Bank Rakyat (2002)
Communications	DiGi Telecommunications Sdn Bhd	• Teradata's data warehousing solution is used to support analytical business intelligence for better understanding of its customers. • BI solution allows the company to analyze customer data related to call detail records and communications management.	DiGi (2009)
Education	Universiti Tun Abdul Razak (UNIRAZAK)	• The university uses BI to enhance performance of administration and operations, such as staff performance and business unit. • BI assists management to monitor KPIs accurately and generate timely performance reports to improve the efficiency of the university.	UNIRAZAK (2010)
Government	Inland Revenue Board (IRB)	• IRB uses SAS Business Intelligence to analyze tax collections faster and understand the revenue impact of proposed tax changes. • Users are able to access data to perform ad hoc queries and analysis, check data inconsistencies easily, and react quickly to changing requirements.	Inland (2010)
Healthcare	Realmild (M) Sdn Bhd	• This company has used BI solutions provided by SAS to enhance strategic planning and budgeting processes of its Group's business operations, such as healthcare facilities management, and logistics and capital management businesses. • Non-productive processes such as manual data entry and data consolidation are eliminated through the use of SAS data integration and analysis technology.	Realmild (2009)

Table 2.5 (Continued)

Industry	Company	Descriptions of BI Usage	Source
Insurance	Insurance Services Malaysia Berhad (ISM)	• SAS Enterprise BI server is implemented on ISM databases to meet the business requirements and improve its operational efficiencies. • SAS analytical capabilities are included in ISM system to provide users with self-service functionality to produce customized reports containing statistical and analytical information to make informed decisions.	ISM (2010)
Manufacturing	Ricoh Malaysia	• This imaging and printing company has used Cognos TM1 BI solution provided by IBM to identify new business opportunities and better manage its budgets. • Data warehousing (IBM Cognos reporting tools and MS SQL 2005) is implemented for business and monitoring control while IBM's business analytics is used for financial performance management.	Ricoh (2010)
Retail	Senheng Electric (KL) Sdn Bhd	• Senheng implemented enterprise data warehouse using Microstrategy software to store transaction data collected from all outlets and transform it into information such as sales, inventory, customer, and finance. • The implementation of BI system helps Senheng to improve stock turnover by optimizing cash flow and to react quickly to business issues pertaining to customers and outlets.	Senheng (2010)
Service	Genting Malaysia Berhad (GMB)	• In order to gain and improve customer insights, GMB implemented SAS enterprise reporting to obtain timely and consolidated KPIs information. • SAS Analytics is also used to improve customer segmentation, customize marketing campaign and optimize resources.	Genting (2010)

For instance, the communication industry uses predictive analytics to identify high-potential subscribers that can maximize BI investment by analyzing existing customer behaviour and demographic data. Banking organizations apply data mining techniques to perform fraud analysis and improve risk management while retail organizations utilize forecasting capabilities to estimate customer demand on products.

Generally, BI usage as depicted in Table 2.5 can be categorized into several types as follows:

- **Reporting and query:** Users can easily access the information they need in real time to generate detailed reports and perform query against data warehouses in order to get immediate answers to their specific business questions. Malaysia's Inland Revenue Board is a good example. This tax revenue collecting board uses the reporting and query model to obtain clearer picture of taxpayers who are more likely to under-report their income tax. Furthermore, the time used to produce complex reports is reduced from two weeks to three days following the adoption of BI tools. This has helped the revenue board to identify underpaid taxes and perform tax collections faster.
- **Ad hoc analysis:** With the use of BI tools, users can immediately perform ad hoc analysis on data and information from multiple sources to improve their key business areas such as customer profitability analysis, sales and marketing analysis, communications management, and tax collection activity. For

instance, Bank Kerjasama Rakyat Malaysia Berhad uses analytical reporting solution to find out the most profitable customers by performing customer analysis and profitability analysis. Through these kinds of analyses, the bank has gained benefits such as improved product performance and better customer relationships. DiGi Telecommunications Sdn Bhd implements enterprise data warehouse to gain deeper insights into products and customers through analysis on data such as call detail records, which can help DiGi to deliver services more effectively.

- **Data mining:** It is commonly used for marketing, finance, and manufacturing. It allows management to view and analyze data from multiple perspectives to quickly identify useful information (patterns, relationships, and trends) hidden within large amount of data which might benefit or threaten an organization. For instance, Insurance Services Malaysia Berhad utilizes data mining techniques to manage and detect potential insurance fraud in order to increase operational efficiencies.
- **Planning:** BI tools facilitate better planning of strategies and resources through effective analysis of data such as customer demographic data and sales data. This helps to uncover new business opportunities, managing revenue, and improving cost efficiencies. For instance, Genting Malaysia Berhad uses advanced analytics to understand frequency of visits and spending patterns of different customer segments for resource

allocation (e.g. memberships and accommodations) and operations planning (e.g. marketing activities and products development). This helps the company to better manage its resources by channelling programs and services with appropriate resources as well as to increase operational efficiencies.

- **Forecasting:** Users can use predictive analytics to accurately anticipate future needs (e.g. products and services) and outcomes (e.g. what will happen if the trends continue). For instance, Insurance Services Malaysia Berhad applies predictive analytics to identify the most profitable product in its insurance profiles. By doing so, it is able to achieve competitive edge.
- **Optimizing:** Managers can optimize daily operations and processes by monitoring the usage of resources (such as inventory, finance, technology, and human resource) and determining which business area requires improvement. Senheng Electric (KL) Sdn Bhd is one of the examples that leverage this optimizing capability to monitor stock movement across all outlets and optimize the cash flow. Stock turnover is improved as a result of better resource optimization.
- **Budgeting:** BI tools enable business users to proactively control costs and improve budgeting process over time by comparing budgets with their actual execution and expenditure (e.g. marketing campaign and manufacturing). Realmild (M)

Sdn Bhd is a good example of organizations that uses this feature to reduce the cost of budget preparation, thereby helping the company to save operational costs.

- **Monitoring:** Organizations can actively track performance and progress toward defined goals by analyzing performance measures and metrics. This can be done through the use of data visualization tools consisting of interactive charts and graphs such as dashboards and scorecards. This enables users to gain valuable insights into customers and business performance. It also helps to improve efficiency and effectiveness of business activities. For example, Universiti Tun Abdul Razak monitors its performance through the use of key performance indicators. This helps the university to identify potential problematic areas through detailed view of performance targets and achievements.

Overall, it can be concluded that BI tools have provided a wide range of capabilities that allow Malaysian organizations, regardless of size and industries, to support their specific business needs. By applying various BI capabilities, organization can leverage information more effectively and thus gaining data-driven insights to drive their decisions.

In relation to the research question, it can be seen that the way Malaysian organizations make use of BI capabilities is associated with maturity level. Having a higher BI maturity level implies that the organization is fully utilize the potential of BI tools to its full capabilities.

2.6 Business Intelligence Maturity Models

Maturity model is "a framework that describes, for a specific area of interest, a number of levels of sophistication at which activities in this area can be carried out" (Tapia et al., 2007, p. 203). A well-developed maturity model is useful for an organization to evaluate its current stage of operations and control implementation progress based on a set of defined criteria (de Bruin et al., 2005). There are numerous BI maturity models developed by academicians and practitioners in order to measure BI capabilities of an organization. These models differ from each other in terms of the number of maturity levels or stages, scope, structures, components, and characteristics. Generally, maturity models have properties as follows (Klimko, 2001; Weerdmeester et al., 2003):

- The development of an entity (for example, human, organizational function, technology) is simplified and described with a limited number of maturity levels (usually four to six),
- levels are characterized by certain requirements that have to be achieved by the entity on that level,
- levels are ordered sequentially from an initial level to an ending level, and
- the entity moves from one level to the next one during development.

Usually, maturity models are used to assess the as-is situation, to derive and prioritise improvement measures, and to control the progress of implementation (Iversen et al., 1999). It is assumed there existed predictable patterns in the evolution of organisations, which are called as evolutionary stages (Gottschalk, 2009). These models provide a roadmap to organisations for improvement in which each level will have better state than the previous level (Fisher, 2004). Besides that, maturity models can be used to develop an approach that can help an organization to boost the capability of a specific area (Ahern et al., 2004).

There are several BI maturity models developed by academicians and practitioners to help organizations in assessing their current position, establishing desired state of maturity, and evaluating progress against established benchmarks. These models differ from each other in terms of the number of maturity levels or stages, scope, structures, key dimensions, and characteristics. 10 commonly used BI-related maturity models include:

- Capability maturity model (CMM)
- Analytical maturity model
- BI development model
- Business information maturity model
- Data warehousing process maturity model
- Data warehousing stages of growth model
- Gartner’s BI and performance management maturity model
- HP’s BI maturity model
- Ladder of business intelligence

- TDWI's BI maturity model

2.6.1 Capability Maturity Model

Capability maturity model (CMM), a well-known software process improvement model, was developed by Watts S. Humphrey and his team members from Software Engineering Institute (SEI) of Carnegie Mellon University in 1986 (Paulk et al., 1993). CMM is structured into five maturity levels: initial, repeatable, defined, managed, and optimizing. There are several key process areas in each maturity level, except for Level 1, that will determine which areas an organization needs to focus on to improve the software development process. Figure 2.4 shows the model of CMM.

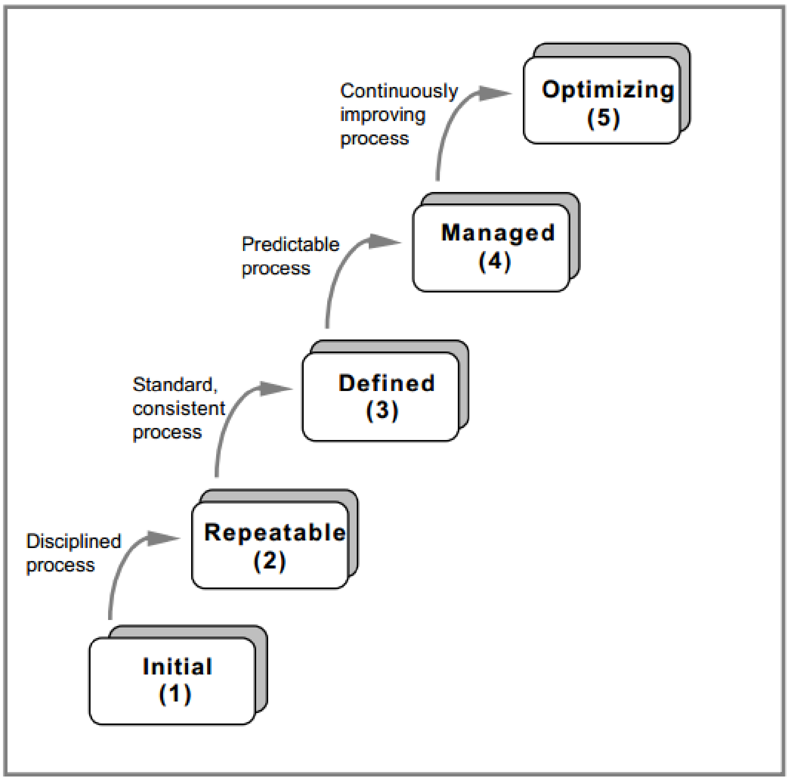


Figure 2.4: Capability maturity model

Source: Paulk et al. (1993, p. 8)

Numerous studies have been written about development of maturity model based on CMM for organizations to measure their maturity of practices in many areas, such as software process, information quality, project management and data warehousing. For instance, Information Quality Management Maturity Model (IQM-CMM) proposed by Baskarada et al. (2007), Strategic Alignment Maturity Model (SAMM) developed by Luftman (2000) for assessing alignment between business and IT, and Data Warehousing Process (DWP) maturity presented by Sen et al. (2006) are based on the concept of CMM to define maturity levels. Whilst de Bruin and Rosemann (2005) developed a five-stage Business Process Management (BPM) maturity model, and Ryu et al. (2006) proposed Data Quality Management maturity model. The abovementioned maturity concepts are similar to CMM.

Apart from that, CMM has also been adapted in the BI context, such as BI maturity model proposed by Raber et al. (2012) and Sayyadi et al. (2012). Although CMM was originally used to improve the quality of software development processes, it could provide a quick understanding of essential elements for effective BI processes from different perspectives by dividing the whole process into different levels and considering different maturity aspects.

2.6.2 Analytical Maturity Model

Analytical maturity model which is illustrated in a pyramid-shaped model as shown in Figure 2.5 consists of five stages, namely analytically impaired, localized analytics, analytical aspirations, analytical companies, and analytical competitors. This model helps organizations to evaluate the state of analytics based on three dimensions, namely organization, human, and technology.

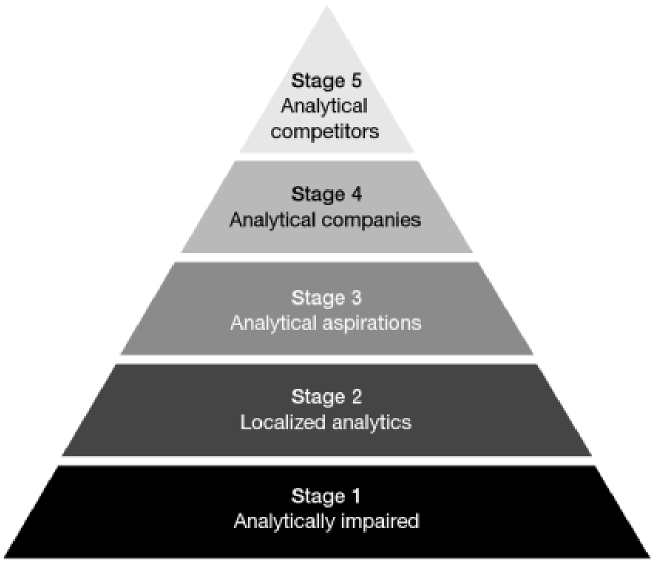


Figure 2.5: Analytical maturity model

Source: Davenport and Harris (2007, p. 35)

The concept of this model can be applied to BI context as analytics is the subset of BI which could drive organizations towards data-driven decision making (Davenport and Harris, 2007). As such, this model can assist the organizations to identify improvement steps to strengthen their analytics culture and capabilities.

2.6.3 BI Development Model

Sacu and Spruit (2010) developed a six-stage BI development model as shown in Figure 2.6 that relates the current BI maturity stages and corresponding characteristics. In order to differentiate and give better understanding of each stage, this model includes 20 characteristics related to BI area and groups them into six different categories, namely temporal characteristics, data characteristics, decision insights, output insights, BI-process approaches, and other characteristics.

This model focuses mainly on analyzing the technology aspect of maturity. In addition, it does not provide specific guidelines for improvement, thus it is insufficient for organizations to align their resources if just based on technology aspect.

Characteristics		Predefined Reporting	Departmental DW	Enterprise-wide DW	Predictive Analytics	Operational BI		BPM
	Stages →					Data Analytics	Embedded BI	
Temporal Characteristics	**Focus:**							
	-historical	x	x	x	x			x
	-near real-time					x		x
	-real-time						x	x
	Refreshing period:							
	-periodically		x	x	x			x
	-near real-time					x		x
	-real-time						x	x
	Action type:							
	-static	x	x	x	x	x		x
	-dynamic						x	x
Data Characteristics	**Data types:**							
	-structured	x	x	x	x	x		x
	-unstructured						x	x
	Data sources:							
	-files & databases	x	x	x	x	x		x
	-application tools& packages		x	x	x	x		x
	-web based & uncommon					x		x
	-processes						x	x
	Granularity level:							
	-aggregated, summary data	x	x	x	x			x
	-low					x	x	x
Decision Insights	**Decisions:**							
	-strategic			x	x			x
	-tactical	x	x	x	x			x
	-operational					x	x	x
	Analysis:							
	-standard reporting	x						
	-ad-hoc analysis		x	x				x
	-trends analysis			x	x			x
	-data mining			x	x			x
	-predictive modeling				x			x
	-exception handling					x	x	x
	Orientation:							
	-deductive	x	x	x	x			x
	-inductive				x	x	x	x
	Decision making:							
	-manual	x	x	x	x	x		x
	-automatic						x	x
Output Insights	**Output:**							
	-analyses	x	x	x				x
	-recommendations&actions				x	x	x	x
	Visuals:							
	-tables, charts or reports	x	x	x	x			x
	-dashboards&scorecards							x
	-alerts					x	x	x
BI-Process Approaches	**Initiation :**							
	-user driven	x	x	x	x	x		x
	-process driven						x	x
	Process integration:							
	-data centric	x	x	x	x	x		x
	-process centric						x	x
	Processing model:							
	-"store & analyze"	x	x	x	x	x		x
	-"analyze & store"						x	x
	Event stream processing						x	x
	"Closed-loop" environment					x	x	x
Other Characteristics	**Users:**							
	-specialized	x	x	x	x	x		x
	-casual						x	x
	Implementation:							
	-departmental	x	x					
	-enterprise-wide			x	x	x	x	x
	Semantics:							
	-not common	x						
	-common		x	x	x	x	x	x

Figure 2.6: BI development model

Source: Sacu and Spruit (2010, p. 3)

2.6.4 Business Information Maturity Model

Williams and Williams (2007) developed a three-stage maturity model as shown in Figure 2.7. This model covers seven key areas: strategic alignment, process improvement culture, information and analytics usage culture, BI portfolio management, decision process engineering culture, BI/DW technical readiness, and partnership between business and IT. Furthermore, this model focuses on increasing BI importance and defines three key success factors for BI: alignment and governance, leverage, and delivery.

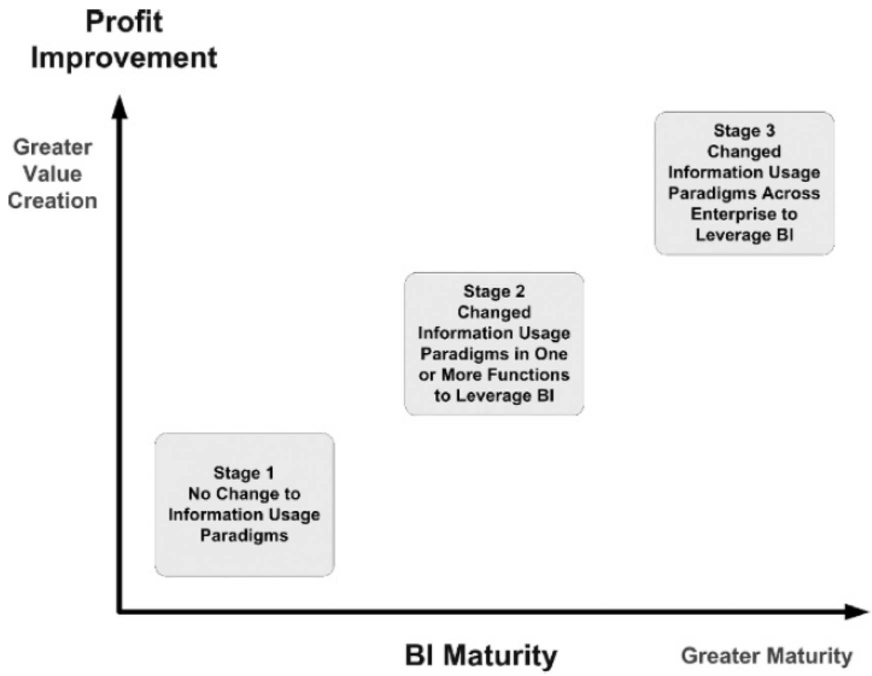


Figure 2.7: Business information maturity model

Source: Williams and Williams (2007, p. 99)

2.6.5 Data Warehousing Process Maturity Model

Sen et al. (2006) describes data warehousing as a process like software development, which can be expressed in terms of components such as artifacts and workflows. Drawing upon the concepts of CMM, they defined five levels for a data warehousing process, namely initial, repeatable, defined, managed, and optimizing as illustrated in Figure 2.8.

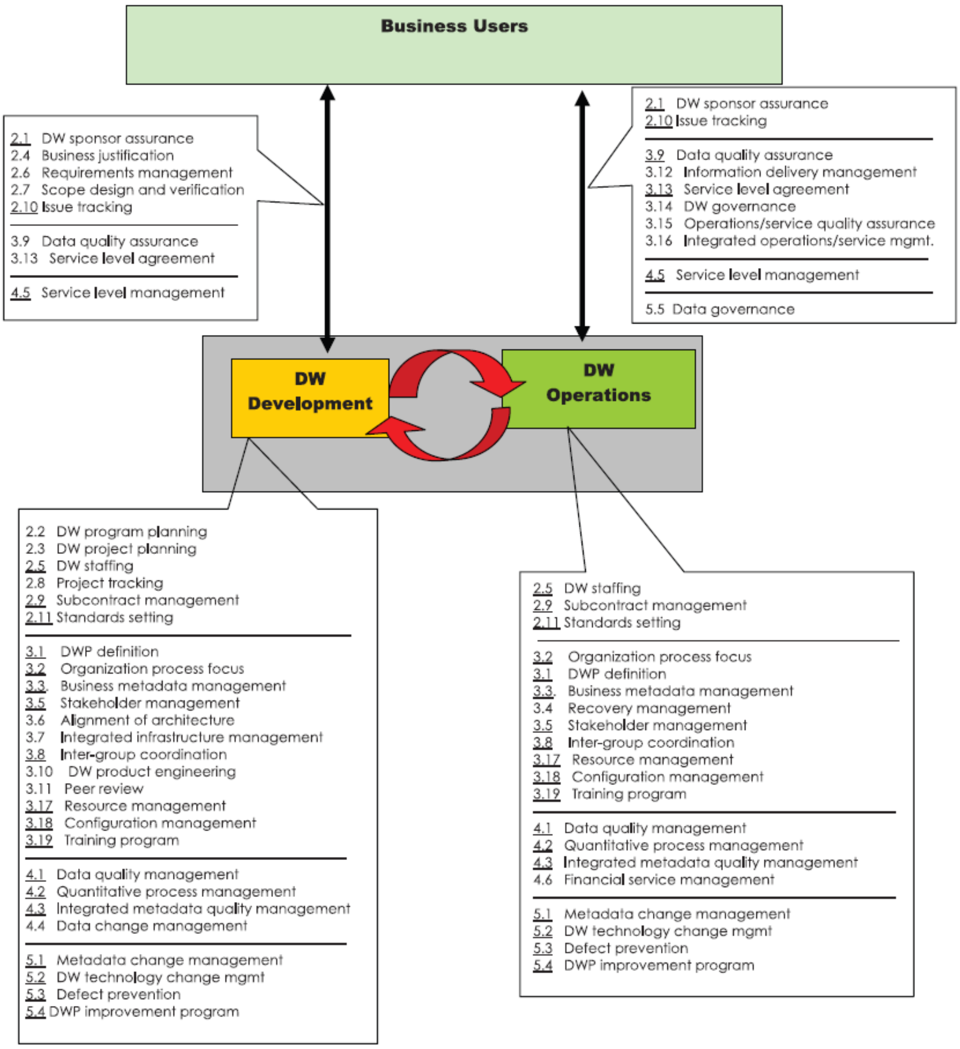


Figure 2.8: Data warehousing process maturity model and key process areas

Source: Sen et al. (2012, p. 348)

Based on an exploratory study, Sen et al. explored the factors influencing perceptions of data warehousing process maturity. The stages of maturity are defined by five key process areas (KPAs): alignment of architecture, data quality, organizational readiness, organizational slack, and change management.

2.6.6 Data Warehousing Stages of Growth Model

Watson et al. (2001b) developed a maturity model for data warehousing (DW) as shown in Figure 2.9. This model consists of three levels namely initiation, growth, and maturity.

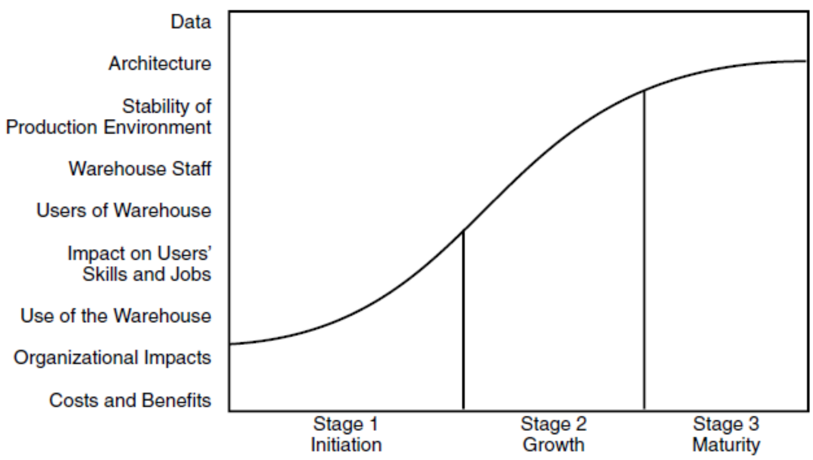


Figure 2.9: Stages of growth for data warehousing

Source: Watson et al. (2001b, p. 45)

There are nine DW specific dimensions, which are data, architecture, stability of the production environment, warehouse staff, users, impact on users' skills and jobs, applications, costs and benefits, and organizational impacts. Additionally, this model is based on the stages of growth concept, a theory describing the observation that many things change over time in sequential and predictable ways.

2.6.7 Gartner's BI and Performance Management Maturity Model

Gartner's BI and performance management maturity model as depicted in Figure 2.10 consists of five levels, namely unaware, tactical, focused, strategic, and pervasive. This model is illustrated in a curve-shaped based on real world phenomenon in which organizational change is usually incremental over time (Hostmann, 2007). The maturity level is evaluated based on a number of business-technical aspects: organizational structure, processes, scope of BI initiatives, sponsorship, metrics, and technology.

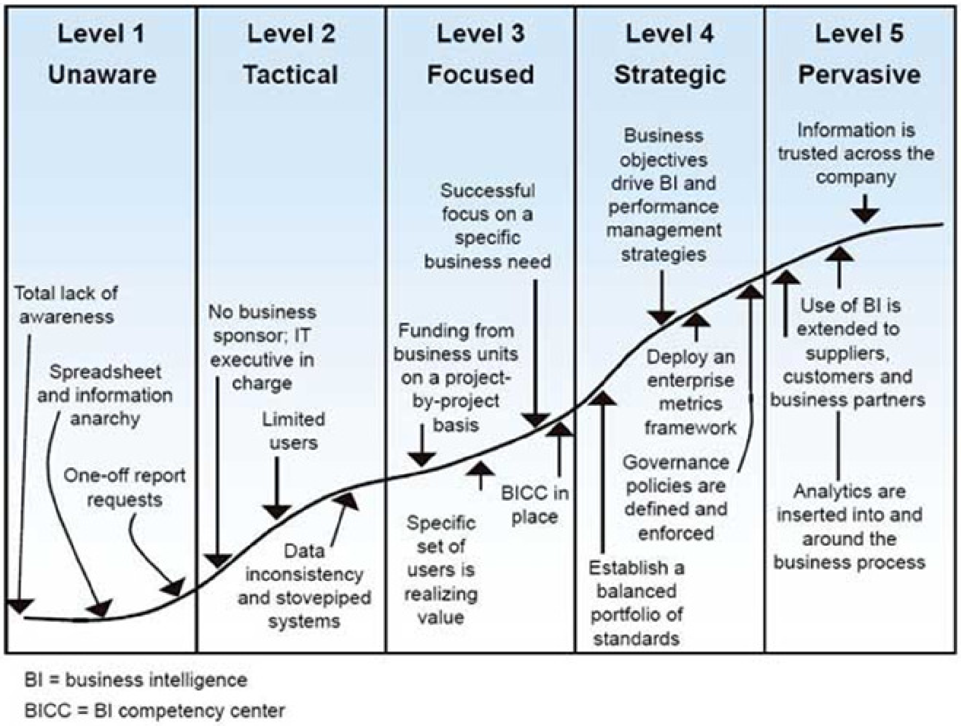


Figure 2.10: Gartner's BI and performance management maturity model

Source: Hostmann (2007, p. 1)

2.6.8 HP's BI Maturity Model

HP developed a BI maturity model in 2007, which consists of five stages, namely operation, improvement, alignment, empowerment, and transformation, which is based on HP's experiences with clients from different industries. This model is represented by a staged structure that describes the evolution of HP clients' BI capabilities. The stages of maturity are evaluated based on 3 dimensions: business enablement, information technology, and strategy and program management (HP, 2012). Figure 2.11 shows the HP's BI maturity model.

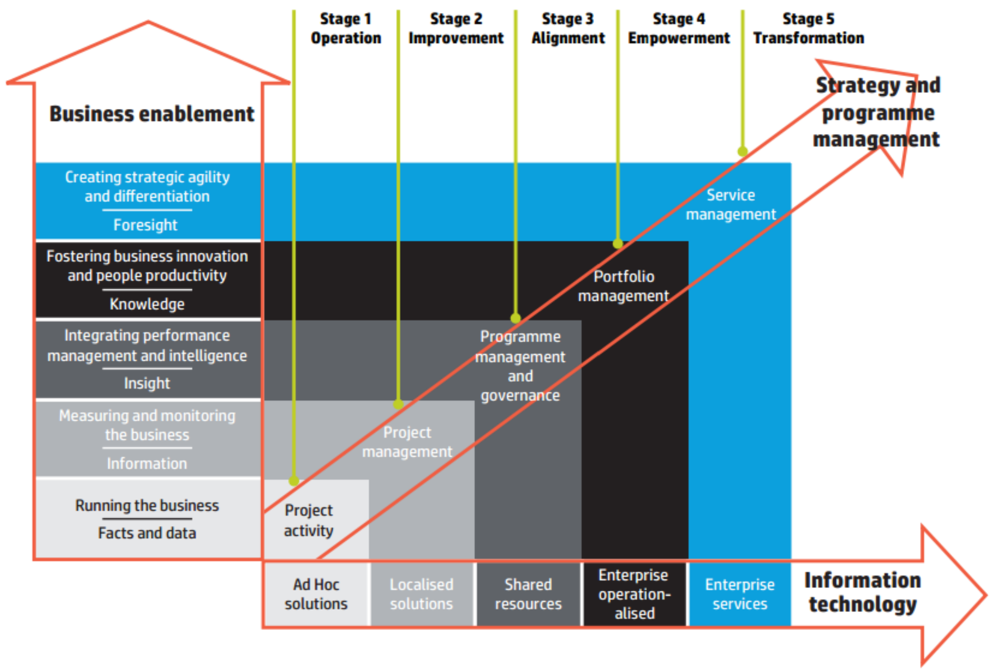


Figure 2.11: HP's BI maturity model

Source: HP (2012, p. 1)

2.6.9 Ladder of Business Intelligence

Cates et al. (2005) developed a BI framework called ladder of business intelligence (LOBI) to improve the IT planning and architecture for a business. This model is part of the LOBI framework, which aims at facilitating the creation of an IT plan and the design of IT architectures. Besides that, other key components of the LOBI framework are the balanced score card, business roles, business processes and technology, cycle time to intelligence, and business role intelligence analysis. The LOBI has six levels and three dimensions, which are not described in detail. This model uses object-centric maturity concept, with information being the object under consideration, with a change to a people-centric maturity concept in higher levels (Lahrmann and Marx, 2010). Figure 2.12 shows the model of LOBI.

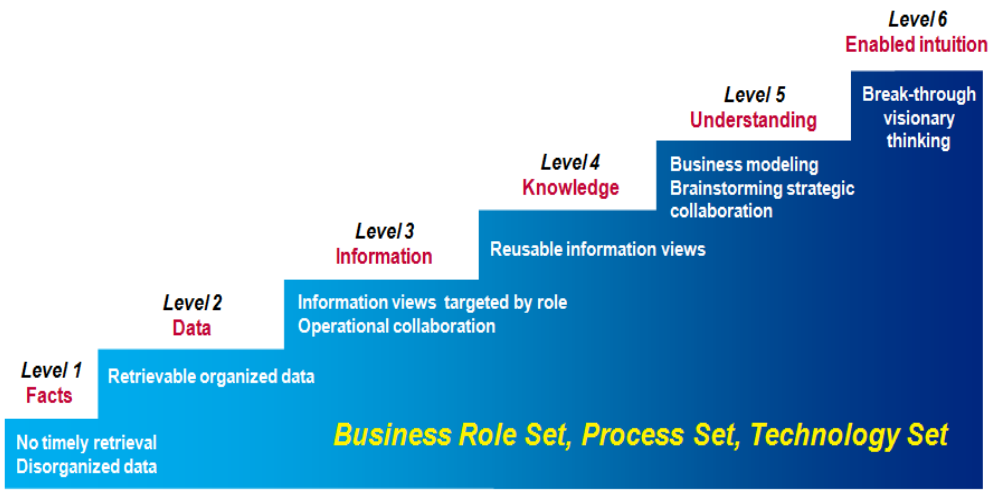


Figure 2.12: Ladder of business intelligence

Source: Cates et al. (2005, p. 227)

2.6.10 TDWI's BI Maturity Model

TDWI's BI maturity model was developed in 2004 by Wayne W. Eckerson, the director of The Data Warehousing Institute (TDWI) Research (Eckerson, 2007b). This maturity model consists of six stages, namely prenatal, infant, child, teenager, adult, and sage, which is based on human evolution analogy. It is illustrated in a bell-shaped curve that indicates the percentage of organizations at a specific stage.

The maturity level of an organization can be evaluated based on eight key dimensions: scope, sponsorship, funding, value, architecture, data, development and delivery. Like the BI development model, this model also focuses only on technology aspect of maturity. In addition, the curves that represent different perspective of BI adoption in this model are difficult for an organization to evaluate its current level in the BI maturity evolution (Sacu and Spruit, 2010). Figure 2.13 shows the TDWI's BI maturity model.

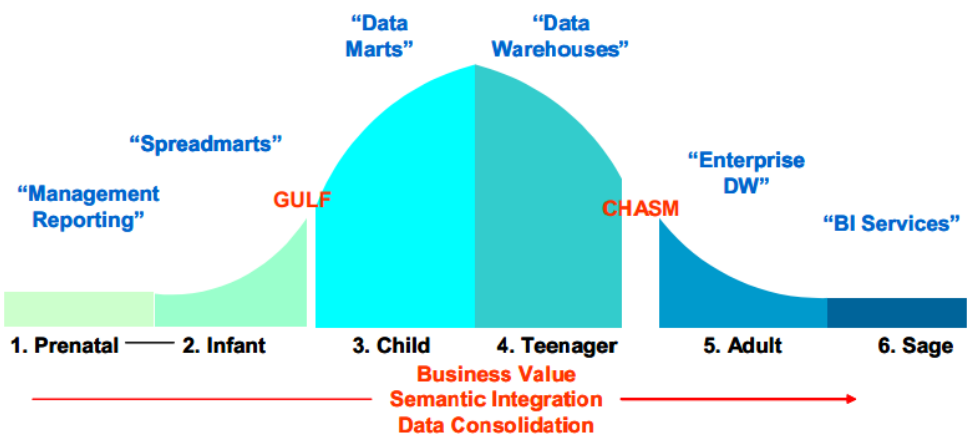


Figure 2.13: TDWI's BI maturity model

Source: Eckerson (2007b, p. 4)

2.6.11 Comparison of BI Maturity Models

Even though these models are commonly used, each has its limitations. First, with the exception of the data warehousing process maturity model (Sen et al., 2006), all of the other four do not explicitly specify the assessment and validation methodologies. The problem of not having the assessment and validation methodologies is that one would not be able to measure the extent to which a BI implementation is successful in achieving pre-established objectives (de Bruin et al., 2005).

Second, the criteria of existing models are not comprehensive enough. Instead, all the five maturity models evaluated here focus only on one or two specific criteria. For example, the data warehousing process maturity model (Sen et al., 2006) concentrates solely on a process perspective whereas the analytical maturity model (Davenport and Harris, 2007) and the HP's BI maturity model (HP, 2012) include only a technology and an organizational perspective. These three maturity models also do not include an outcome perspective that will measure the success of BI implementation efforts. For those that actually include the outcome perspective, they often fail to measure many important dimensions of BI. For instance, although the TDWI's BI maturity model (Eckerson, 2007b) evaluates reporting and business analysis, data quality, and management methodologies, it does not consider performance management. To ensure that organizations gain full benefits from BI, they would need the guidance of a comprehensive BI maturity model that addresses all areas that might be impacted by the implementation of BI.

Third, these BI models (i.e. analytical maturity model, data warehousing process maturity model, TDWI's BI maturity model) lack a focus on organizational issues (e.g. management support, executive sponsorship, strategic alignment). Since organizational issues have a higher impact on the success of BI initiatives compared to technical issues (Howson, 2008), it is critical for a maturity model to include a dimension that measures the extent to which organizational supports are being setup to facilitate BI implementation.

Fourth, most of the models (i.e. analytical maturity model, data warehousing process maturity model, Gartner's BI and performance management maturity model) do not take into account data issues, such as master data management and metadata management, which are important to BI success. Although organizations are aware of the need to manage data as a corporate asset, they are not solving the root cause of data related problems (HP, 2007). The absence of proper data management may lead to problems such as lack of productivity, poor business decisions and performance, and inability to achieve desired results (IBM, 2007; Prouty and Castellina, 2011). The application of metadata management can help to ensure consistency of definitions and descriptions of data (Berson and Dubov, 2010).

Fifth, all of the models, except data warehousing process maturity model (Sen et al., 2006), do not address change management issues. As organizations mature and encounter more frequent changes, they would need to have structured change management processes to ensure that standardized procedures are applied to every new project or new change in a systematic manner (Prosci, 2004). Furthermore, a BI maturity model should also address the different types and states of tools (e.g. OLAP, reporting) as well as the architectures (e.g. data warehousing) needed for efficient and effective functioning of a BI system. As shown in Table 2.6, only four models (i.e. analytical maturity model, Gartner's BI and performance management maturity model, HP's BI Maturity Model, TDWI's BI maturity model) address the tools whereas only two models (i.e. data warehousing process maturity model, TDWI's BI maturity model) address the architectures.

Implication for this research: The components in the existing maturity models and literature were reviewed and assessed. Table 2.6 provides a comparison of the components used in different maturity models. Although it appears that different terms have been used as components, they are mainly related to the following four dimensions: organizational management, process, technology, and outcome. Apart from that, most of the existing BI maturity models have concentrated on the processes and technologies used to collect, store and analyze data.

The review of the extant literature on BI maturity models reveals that CMM and TDWI's BI maturity model are considered as the most suitable reference model for BI implementation. This is evident that CMM has been widely accepted and used to shape various maturity studies in IS research (Sen et al., 2006; Russell et al., 2010). TDWI's BI maturity model can be applied to organizations in different industries and it outlines the path that majority of organizations undertake when evolving their BI infrastructure.

Table 2.6: Comparative analysis of components among BI maturity models

	BI Maturity Models									
Components	**Cates et al. (2005)**	**Davenport and Harris (2007)**	**Eckerson (2007b)**	**Gartner (2007)**	**HP (2012)**	**Paulk et al. (1993)**	**Sacu and Spruit (2010)**	**Sen et al. (2006)**	**Watson et al. (2001)**	**Williams and Williams (2007)**
Architecture			✓				✓	✓	✓	
Change management						✓		✓		✓
Commitment from business and IT				✓		✓		✓		
Data quality			✓	✓			✓	✓	✓	
Data management			✓		✓					
Performance management	✓			✓						
Process		✓	✓	✓	✓	✓		✓		✓
Skills and competencies		✓								
Sponsorship and funding		✓	✓	✓	✓	✓				
Strategic alignment					✓					
Tools and technologies		✓	✓	✓	✓	✓	✓			✓
Vision and goals	✓			✓						

However, CMM does not take into account the issues in determining the success of BI systems implementation among their quality goals. In view of this, a BI maturity model is proposed to address BI issues and provide a systematic method for organizations to achieve improvement based on the concept of CMM and TDWI's BI maturity model.

As discussed in section 2.2, four dimensions (i.e. organizational management, process, technology, and outcome) have been identified as criteria for the development of the proposed BI maturity model. The BI model is designed to test different aspects of an organization's BI capabilities. By combining these four dimensions, it assesses the overall BI maturity level of an organization. The proposed BI maturity model is presented in Figure 2.14 and is discussed in the following section.

2.7 Proposed Business Intelligence Maturity Model

Drawing on the review of academic and practitioner literature, a comprehensive BI maturity model as shown in Figure 2.14 was developed by using the core-ideas of capability maturity model (CMM) and TDWI's BI maturity model.

Figure 2.14: MOBI maturity model

As can be perceived through Figure 2.14, the so-called MOBI (Malaysian Organizations' Business Intelligence) maturity model incorporates all the components that are critical to measure the BI maturity level of Malaysian organizations but were not found in some of the BI maturity models reviewed in this research (which have been described in section 2.6.11). All the BI related components were then grouped into four dimensions as below:

i. Organizational management

ii. Process

iii. Technology

iv. Outcome

The MOBI maturity model was built in five-point scale (i.e. Initial, Repeatable, Defined, Managed, and Optimizing) which corresponds to the five maturity levels of BI.

2.7.1 Organizational Management

This "Organizational Management" dimension assesses the extent to which the management structure is able to support BI related business processes. Support from senior level management is one of the most important criterions to the success of BI (Wixom and Watson, 2001). Too often, there is limited commitment from business or IT people towards BI initiatives. Most of the underlying BI issues are not just related to technological, but they are more often organizational-related that require higher-level commitment, strategic alignment, and shared accountabilities among stakeholders.

In order to obtain organizational buy-in and support for BI initiatives, it is important to clearly define and communicate strategic vision and plan to key business stakeholders (Williams and Williams, 2007). As the scope of BI initiatives expands, users are demanding more control of their BI environment in meeting changing business needs. Thus, it is relatively paramount to ensure that broader range of BI skills and appropriate governance are in place to provide self-service capabilities (Stodder, 2011). In addition, proper training programmes should be provided to teach the users on all aspects of information access and usage rather than focus narrowly on how to use a BI tool (HP, 2007). There are 11 components in this dimension as shown in Table 2.7.

Table 2.7: 11 components in the Organizational Management dimension

Component	Description
Vision	It is essential to have a well-articulated vision and understood to ensure the implementation of different BI components (e.g. technology, people, and processes) fit together in the overall BI environment. The absence of sensible vision may lead to problems such as failure in organizational change efforts and lack of long-term opportunities (Lipton, 1996).
Goals	It is necessary to have a set of specific BI goals to support BI visions and manage BI activities. In the absence of a clearly articulated and up-to-date set of objectives, the BI team needs to spend significant time interviewing departmental executives and corporate executives to understand the mission and direction of their group before they can begin with the actual work of defining KPIs. Therefore, management must have a strong incentive to identify specific business objectives and goals and to communicate these to everyone in the organization (Miller, 2007).

Table 2.7 (Continued)

Component	Description
Scope	It is necessary to clearly define the BI coverage so that proper funds and resources can be allocated to match the scope of BI project. The scope of BI needs to expand outward to include suppliers, business partners, and customers. As the BI solution gains the confidence of executives and users, it will be expanded to a mature enterprise resource that serve many departments and provides cross-functional views of the data (Eckerson, 2003).
BI awareness	BI awareness describes the company-wide understanding of BI capabilities. It is vital to expand BI awareness so that organizations will be able to reap full benefits of BI and maximize return on their BI investment.
Strategic alignment	In order to be in higher levels of BI maturity, there must be alignment between the business and BI. It is important for an organization to have a BI strategy that aligns with business strategy and is being updated when necessary. However, most organizations do not have a clear BI strategy and are still struggling to address the fundamental challenges of BI.
Business commitment	Commitment from business people is a necessary condition for BI implementation success and their involvement is an excellent indicator of that commitment (Reinschmidt and Francoise, 2000). Many BI projects fail because of unavailable or unwilling business representatives (Atre, 2003). So, business people should actively involved in BI initiatives to drive business requirements.
IT commitment	A successful BI implementation requires continuous participation and commitment from both IT and business (Reinschmidt and Francoise, 2000). IT people should have equal roles as business people in defining the business strategy.
Governance	Without a properly defined governance process, BI initiative will probably fail or cannot adapt and respond quickly to changing business requirements. According to Watson and Wixom (2007), organizations that are in higher level of BI maturity have effective BI governance that ensures that all aspects of BI, ranging from strategic alignment with the business strategy to the establishment of common data definitions, are handled effectively.
Skills and competencies	According to Atre (2003), one of the challenges for BI success is that lack of skilled and available staff. The level of skills and competencies can affect the performance and ability of an organization to adapt to continuous changes. Different sets of skill sets may help BI projects more successfully meet their objectives at a project level. A highly skilled project team will have better equipped to manage and solve technical problems (Wixom and Watson, 2001).

Table 2.7 (Continued)

Component	Description
Training	Employees need to be trained in using BI system and other tools to ensure that they can utilize the full potential and capabilities offered by these tools. In addition, training for individuals to understand their new roles for performing BI tasks and run the business processes might be needed.
Sponsorship and funding	Senior management has to perceive and treat BI as a strategic resource in order to achieve a high level of BI maturity. The most effective sponsors should be top business executives who have considerable influence in the organization as well as possess a vision for how BI can be used to achieve key business strategies or address critical business problem and opportunities (Eckerson, 2003).

2.7.2 Process

The focus of this "Process" dimension is to find out how an organization can coordinate and execute BI activities more effectively (Aho, 2009). Frequently, requirements for BI initiative are 'ad hoc' and change over time. So, it is necessary to have good governance and change management to make sure the overall BI initiative is consistent and able to respond to changes quickly (Hawking and Sellitto, 2010).

Another major issue that IT leaders face in BI implementation is inadequate metadata management capabilities. Metadata is a basis for decision making that provides background about data within BI environment (Tvrdíková, 2007). Poorly managed metadata could lead to problems such as limited data sharing, decrease the efficacy of BI initiative, and increase data-related risk (Swoyer, 2010). This dimension includes five components as revealed in Table 2.8.

Table 2.8: Five components in the Process dimension

Component	Description
Implementation	Many BI projects fail because of no work breakdown structure, that is, no methodology (Atre, 2003). BI projects are characterized by ambiguous and dynamic requirements, with uncertain technology components, data integration challenges, and other obstacles (Sabherwal and Becerra-Fernandez, 2009). The BI implementation process has to be iterative, agile and adaptive to change so that the project implementations can be organized and managed effectively (Reinschmidt and Francoise, 2000; Pant, 2009b).
Change management	Getting users to embrace the change each project brings is one of the major challenges faced by a typical organization. Most of the requirements that drive the implementation of BI will change over time. So, having a proper change management is critical to BI initiatives. Formal user involvement in the process of change can lead to better communication of organization's needs, which in turn can help ensure successful BI implementation.
Master data management (MDM)	Within every organization, there is a set of data that provides valuable information to identify and uniquely define core business data entities, such as customers, products, and suppliers. These master data are shared by multiple applications across the organization. However, due to the proliferation of enterprise applications, this has resulted in master data being scattered across the organization. In order to evolve to a higher maturity level, there is a need for deploying MDM to provide a single, synchronized view of key data entitles for common use (Loshin, 2007).
Metadata management	One of the barriers for BI success is that there is no understanding of the necessity for and the use of metadata (Atre, 2003). As the scope of BI implementation increase, organizations need to recognize that metadata is the key to guiding analysis to use the correct and most effective information. Good management and use of metadata can reduce development time, simplify on-going maintenance, and provide users with information about data source (Bryan, 2009).

Table 2.8 (Continued)

Component	Description
Data governance	Usually, organizations in the early stage do not have ownership of data, that is, lack of data governance. This leads to the problems associated with data quality, subsequently affect the BI implementation. According to Pant (2009b), effective data governance can ensure that organizations achieve the goals of increasing confidence in decision making, making the data universally visible throughout the organizations, and instilling confidence in users that the data is accurate.

2.7.3 Technology

The “Technology” dimension measures the extent to which BI tools and architectures are being deployed to provide a better understanding of business processes (Foley and Manon, 2010).

Increasing volumes of available data and greater expectations for decisions demanded more sophisticated and powerful BI technologies to increase return on investment (ROI) in BI environment. As such, the trend towards technologies such as cloud computing, Big Data, predictive analytics, and in-memory analytics has arrived in the BI domain (Bates and Wall, 2012). These technologies could enable better business outcome and improvement of BI performance, thereby increasing organizations’ level of BI maturity. There are a total of six components in this dimension as depicted in Table 2.9.

Table 2.9: Six components in the Technology dimension

Component	Description
Data warehousing	As organizations become more automated and data-driven, the data warehousing architecture must evolve to support operational decision making at all levels in the organizations (Dayal et al., 2009).
Master data architecture	It is necessary to have solid, flexible master data architecture to support operational uses by ensuring the data is up-to-date, complete and validated (IBM, 2007). If the master data architecture is not defined, there will be many replicated copies of data sets which relevant to more than one application exist, thus causing failure of data sharing between applications (Dyche and Levy, 2009).
Metadata architecture	There are many types of metadata have to be managed in the architecture, such as business metadata, operational metadata, and technical metadata. Without appropriate controls, metadata evolves inconsistently across the organization resulting in pockets of complex, isolated, undocumented, and non-reusable metadata components tightly coupled with individual applications and systems (Shankaranarayanan and Even, 2004).
Extract-Transform-Load (ETL)	As BI system evolves over time, the ETL processes should be automated, flexible and reusable so that changes can be made easily (Watson et al., 2006). There are few aspects that need to be taken into consideration for ETL processes, such as functionality, performance, scalability (i.e. the ability to handle high volumes of data), freshness, and flexibility (Dayal et al., 2009).
Online Analytical Processing (OLAP)	OLAP allows users to easily compare different types of data and complex computations. However, large amounts of data can affect OLAP goals such as accuracy and timeliness of that data. Thus, it is needed to have more advanced OLAP capabilities (e.g. powerful calculation, flexible analysis, multi-user support, fast access) to address the OLAP issues (Thomsen, 2002).
Reporting and analysis	As BI evolves to a higher level of maturity, the degree of comprehensiveness at which data are being processed and presented increases to tailor to increasing complexity in decision-making. However, many users still rely heavily on static operational reports and spreadsheets created by IT to meet specific individual needs. The problems such as lack of flexibility of operational reports may arise because the reports show only a limited range of data for a limited set of processes (Eckerson, 2007b).

2.7.4 Outcome

The “Outcome” dimension examines the results of implementing BI components, such as management, processes, tools and architectures (Pant, 2009a). This study identifies data quality, information quality, and key performance indicators (KPIs) as the outcomes of successful BI implementation. Data quality continues to be a critically important issue. As data volumes are constantly increasing, it becomes more difficult for many organizations to validate and maintain data accuracy, timeliness, completeness, and consistency (March and Hevner, 2007).

Sabherwal and Becerra-Fernandez (2009) stated that information is the product of BI that leads to knowledge and facilitates decision making. As BI is dependent on the flow of information, it is essential that information quality aspect is regarded when measuring BI maturity.

Additionally, key performance indicator (KPI) is another most important criterion in evaluating BI capabilities of organizations. KPIs must be of appropriate quality as incorrect KPI results would lead to poor decision making (Masayna et al., 2007). This dimension contains three components as shown in Table 2.10.

Table 2.10: Three components in the Outcome dimension

Component	Description
Data quality	Data quality continues to be a huge concern for organizations. When data are of inadequate quality, the knowledge workers and decision makers do not trust the results and decisions (Manjunath et al., 2011). In order to obtain clean and reliable data, it is imperative to have a single version of the truth as well as people and processes in place to ensure and enhance the quality of the data (Watson and Wixom, 2007).
Information quality (IQ)	Burns (2005) indicated that IQ is an important factor for BI and that IQ often was a source of failure. The quality of decisions and actions depend on the quality of information (Stvilia et al., 2007). In order to achieve higher level of information quality, it is important to conduct continuous quality assessment and address areas that need improvement.
Key performance indicators (KPIs)	KPIs differ for departments and business units depending on the nature of business and business strategies but in all enterprises these KPIs align with the overall goals of the business. Generally, KPIs are focused either on critical aspects of organizational performance that require improvement, or on the aspects that must be kept within a specified level to ensure continuous success of the organization (AusIndustry, 1999).

2.8 Related Work on the Influence of Demographic Variables on the BI Maturity Level

There is limited research on the influence of demographic variables on the BI maturity level. The literature has attempted to improve understanding on the business value of BI and the drivers of BI adoption. However, limited attention was paid to identify what contextual factors affect organizations' BI maturity level in the first place. The study of Raber et al. (2013) highlighted that evolution of BI maturity in organizations is influenced by two key contextual factors namely environment (i.e. industry type) and company size (i.e. number of employees).

The study of Elbashir et al. (2008) showed that industry type (i.e. service and non-service industries) had an impact on the evolution of BI maturity. Ramamurthy et al. (2008) revealed that not all organizations implement BI to the same degree of sophistication as diverse industries have different needs and expectations from BI innovation, thus will implement it at different pace. For instance, organizations in non-service industry (e.g. manufacturing) are more likely to adopt more complex BI tools than the service-oriented organizations. Additionally, the study of Shanks et al. (2012) also highlighted that service industries are very information-intensive, requiring more scrutinizing and reporting functionalities to address explorative and routine problems than non-service industries. During earlier stages of BI implementation, service organizations focus on technical infrastructure aspects while non-service organizations focus on governance and standardization aspects (Raber et al., 2013). This was also supported by Marjanovic (2007) and Vukšić et al. (2013) in which business processes in service industries are usually customer-driven and more difficult to standardize compared to operational processes in non-service industries. Hence, it can be inferred that these differences between industries may have significant effects on the BI maturity.

In particular, larger organizations often have more manpower and strong financial resources to ensure their BI alignment and support needs are being met (Ramamurthy et al., 2008; Sabherwal and Becerra-Fernandez, 2009). This was also pointed out by Malladi (2013) who said that large organizational size are more able to invest in different activities that support BI. Although smaller organizations may possess a few capabilities (e.g. develop BI solutions using agile approach) at an earlier stage, they are not likely to achieve well as large organizations, especially in term of BI strategy and technical infrastructure (Raber et al., 2013). Small- and medium-sized organizations are constrained by obstacles in term of cost and complexity such as tighter budgets, lack of in-house expertise, and technology hurdles (Malladi, 2013). This restricts their abilities to enhance organizational performance and achieve competitiveness of businesses. Therefore, larger organizations tend to attain higher BI maturity level than smaller organizations. Consistent with the discussion, this research hypothesizes that the organizational size has a significant effect on the BI maturity.

In addition to organizational size, prior studies also suggested that age of BI initiatives (i.e. length of time organizations have been using BI system) has an effect on BI maturity level. The study of Eckerson (2007a) and Dekkers (2007) reported that BI initiatives that have existed for longer period of time indicate a high level of maturity. As such, organizations with more BI experience are able to develop expertise and skills to use BI system more effectively in producing business benefits than those with less BI experience (Elbashir et al., 2011). This was also supported by the study of Dekkers (2007) who found that organizations with greater time since adoption of BI system are more mature in coordinating their BI activities such as funding. For example, most organizations in early stage of BI maturity treat the costs of BI systems as overhead. In contrast, those organizations in advanced stage allocate BI costs using subscription-based billing (i.e. pay-per-use) approach where the costs are distributed fairly to each user group (e.g. heavy and light users) based on usage levels.

2.9 Conclusions

This chapter presented an introduction, definitions, and an overview of BI and maturity model. The review of the literature on these topics had aided in developing a thorough understanding of prior related studies for the creation of a multi-dimensional BI maturity model. In addition, the exploration of existing literature had provided an insight into research approaches, strategies, and techniques for this research. Furthermore, the literature review also serves as a source of comparison of findings from previous studies with this research. This chapter also discussed the proposed BI maturity model (i.e. MOBI maturity model) by using the core-ideas of capability maturity model (CMM) and TDWI's BI maturity model.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the research methodology employed in this research. It starts with the research design, and followed by the explanation and justification of the research paradigms such as positivism, interpretivism and critical theory. Next, it describes the research approaches, quantitative versus qualitative research methods, research samples, research instrument, data collection procedure, and data analysis.

3.2 Research Design

Research design is "the overall plan for relating the conceptual research problem to relevant and practicable empirical research" (Ghauri and Gronhaug, 2005, p. 56). The starting point in developing a research design is to determine an appropriate paradigm (e.g. positivism, interpretivisim, critical, pragmatism, etc.) followed by a research methodology (e.g. quantitative, qualitative, and mixed method) and then a set of research methods (e.g. experiment, survey, and case study). An appropriate research design is important as it connects a methodology and a suitable set of research methods in order to address research questions and or hypotheses that are established to examine social phenomena (Wahyuni, 2012).

This research was divided into three main phases namely establishing a conceptual background, developing a BI maturity model, and testing the BI maturity model through preliminary and empirical studies. Preliminary study is crucial as it pre-tests the research instrument to identify potential problems which could influence the research process and validity of the results (van Teijlingen and Hundley, 2002). Meanwhile, the purpose of conducting empirical study is to ascertain and discover facts based on systematic collection of data and observation, rather than relying on ideas or theories (Neuman, 2011).

Figure 3.1 illustrates the research design framework used in this research. In the context of this research, cross-sectional questionnaire-based survey is used to conduct a quantitative enquiry in deductive way within the positivism research paradigm. The selection of research paradigm, approach, and method are discussed in detail in sections 3.3 through 3.5. Then, the details on the process of data collection and analysis are presented in sections 3.6 through 3.8 and 3.9, respectively.

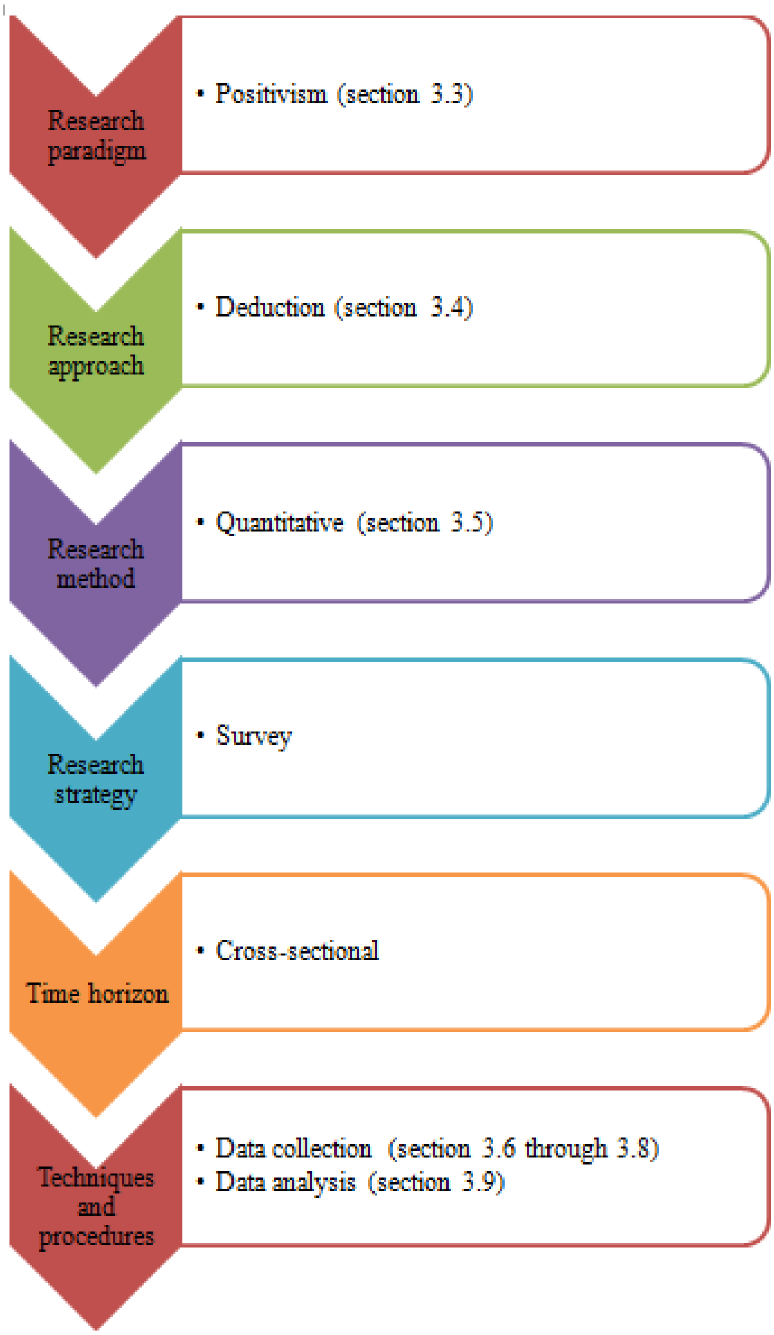


Figure 3.1: Research design framework in the research

3.3 Research Paradigm

According to Mingers (2001), research paradigm is “a construct that specifies a general set of philosophical assumptions covering, for example, ontology (what is assumed to exist), epistemology (the nature of valid knowledge), ethics or axiology (what is valued or considered right), and methodology" (p. 242). In general, information system (IS) research can be classified into three main paradigms: positivism, interpretivism, and critical theory (Klein and Myers, 1999; Myers and Avison, 2002; Neuman, 2011). The selection of research paradigm is influenced by the context of the researcher, research questions to be answered, and research enviroment (Trauth and Jessup, 2000).

3.3.1 Positivism Paradigm

Most of the past IS studies adopted positivism research paradigm that aims to test theory and to gain a better understanding of phenomena (Myers, 2013). According to Orlikowski and Baroudi (1991), IS research is classified as positivist if there was "evidence of formal propositions, quantifiable measures of variables, hypothesis testing, and the drawing of inferences about a phenomenon from the sample to a stated population" (p. 5). Positivist researchers assert that the process of scientific research should be objective (i.e. based on facts and reasoning) and unbiased (i.e. free from value judgements) (Neuman, 2011).

In this research, positivism was judged to be the most appropriate paradigm for the collection, analysis, and interpretation of data. As such, it allows the researcher to evaluate an explanation by logically deducing from theory and by using quantitative data collection to test hypotheses.

Furthermore, information regarding BI maturity can only be measured through objective methods rather than being inferred subjectively through intuition or sensation, thereby warranting a positivism approach.

3.3.2 Interpretivism Paradigm

Generally, interpretive researchers concentrate on understanding and interpretation of phenomena through social constructions and meanings that participants assign to reality (Myers, 1997). These social constructions include observations, language, consciousness, and symbols which are expressed through participants' voices, perceptions, activities, beliefs, and behaviours (Trauth and Jessup, 2000).

The interpretivism paradigm was deemed unsuitable since this research provides pre-defined dependent and independent variables based on literature reviews instead of relying on human senses to identify variables.

3.3.3 Critical Theory Paradigm

Critical theory studies attempt to critique existing social systems and reveal any issues of power struggles and oppression to improve human well-beings (Myers, 1997). Critical researchers believe that social reality is historically constructed and one's interpretation of a situation is influenced by social, cultural, political, and environmental dominations (Myers, 2013).

The critical theory paradigm was considered to be less relevant because the scope of this research is limited to improved understanding of BI maturity at a conceptual level through analysis of BI literature. Furthermore, this research does not attempt to shape or transform current industry practices, rather it aims to identify and understand the key dimensions that affect the BI maturity.

3.4 Research Approach

Research approach is described "as the path of conscious scientific reasoning, and while following distinct paths, have the common aim of advancing knowledge" (Spens and Kovács, 2006, p. 375). Spens and Kovács added, basically, there are two approaches for acquisition of new knowledge:

- **Deduction:** It is described as a theory falsification or verification process that follows the path from a general theory to a more specific logical reasoning.
- **Induction:** It is described as a theory generation and building process that follows the path from specific facts or empirical observations to general theories.

Figure 3.2 represents the research process framework involving the deduction ('top-down' logic) and induction ('bottom-up' logic) approaches (Johnson and Christensen, 2012).

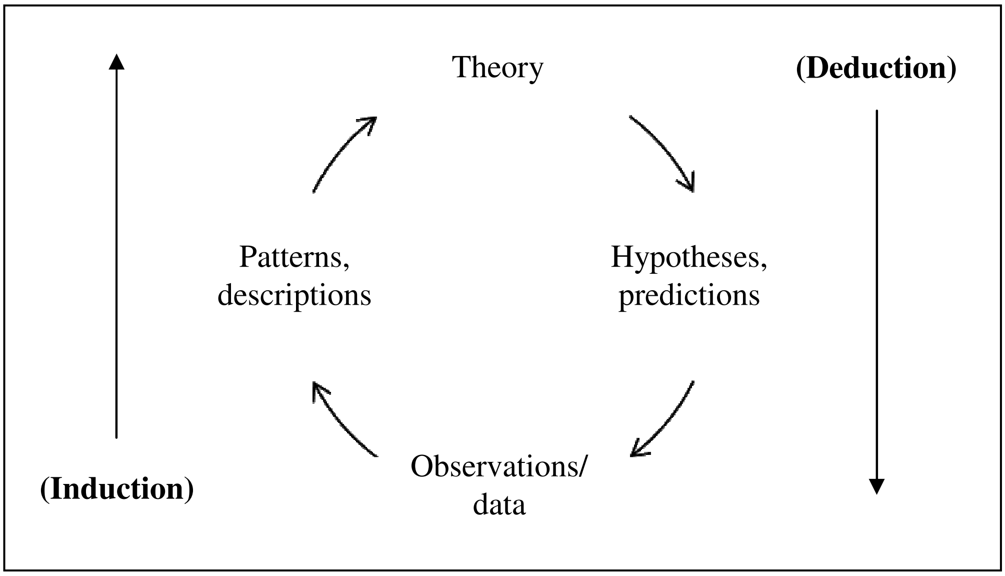


Figure 3.2: The two different research approaches

Source: Johnson and Christensen (2012, p. 18)

This research consists of empirical study that aims to test the proposed BI maturity model, and effect of demographic variables on the BI maturity. Based on this rationale, the deduction approach was chosen as it suits best the structure of this research by connecting past literature and theoretical knowledge with empirical testing. The induction approach was not considered because this research does not attempt to generate new theory, rather seeking to examine the relationships between variables and generalize conclusions.

A thorough investigation of existing literature and theories was conducted to identify the key dimensions and associated components to be built into each maturity level of a BI maturity model. Subsequently, a set of hypotheses in line with research questions were constructed and empirical data collection was used to test the hypotheses. Finally, general conclusions with theoretical knowledge and findings were presented based on the falsification or verification of the hypotheses.

3.5 Research Methods

A research method consists of "techniques and procedures used to obtain and analyse research data, including for example questionnaires, observation, interviews, and statistical and non-statistical techniques" (Saunders et al., 2012, p. 674). There are two broad classifications of research methods:

- **Quantitative:** It is usually "associated with positivism, when used with predetermined and highly structured data collection techniques" (Saunders et al., 2012, p. 162). This method involves the analysis of numerical data using statistical techniques to examine the relationship among variables or hypotheses. In addition, it is often deal with a large sample so that the results can be generalized to a wider population (Creswell, 2013).
- **Qualitative:** Qualitative research method is often linked to interpretivism paradigm (Saunders et al., 2012). It focuses on the analysis of descriptive data to explore and understand different perceptions of individuals or groups towards a particular phenomenon (Creswell, 2013). Only a relatively small sample of participants is involved in qualitative research. (Saunders et al., 2012).

In this research, quantitative research method was regarded as the most appropriate method because qualitative research method does not provide statistical findings that can be generalised to a larger population (Lund, 2005). Moreover, qualitative research method tends to be less structured and relies on individual's point of view which might lead to bias during data interpretation and affect the results (Bryman, 2012). Since this research involves the testing of the formulated hypotheses and theoretical model, hence survey research strategy was conducted to collect large amount of quantitative data through the use of structured questionnaire. In addition, quantitative research method is very useful to this research because it can be used to examine relationships between variables and compare the results with the findings of extant literature, as well as avoid interviewer bias (Muijs, 2010).

3.6 Research Samples

According to Forza (2002), sampling refers to:

> The process of selecting a sufficient number of elements from the population so that by studying the sample, and understanding the properties or the characteristics of the sample subjects, the researcher will be able to generalise the properties or characteristics to the population elements (p. 163).

There are three commonly used techniques to select samples for quantitative research:

- **The convenience sampling:** It is also referred to as haphazard sampling that involves selecting samples that are most easily accessible to the researcher (Teddlie and Yu, 2007).
- **The purposive sampling:** It is also known as judgemental sampling technique “in which the researcher uses a wide range of methods to locate all possible cases of a highly specific and difficult-to-reach population” (Neuman, 2011, p. 267).
- **The simple random sampling:** It is a technique “in which a researcher creates a sampling frame and uses a pure random process to select cases so that each sampling element in the population will have an equal probability of being selected” (Neuman, 2011, p. 249).

The purposive sampling method was employed to select the samples in both the preliminary and empirical studies in this research. It is believed that members of top senior management and operational managers from BI- or IT-related departments were the appropriate persons for selection in this research, as they understand the organizations’ BI environment and make the decisions related to organisational planning. The samples involved in the preliminary and empirical studies were purposively selected because it is believed that the experience of the participants is imperative to obtain valuable BI related information in the selected organisations.

A total of five organizations from three types of industries i.e., banking, tourism and hospitality, and healthcare, participated in the preliminary study. The reason for implementing the preliminary study was to measure the survey instrument in term of reliability and validity (van Teijlingen and Hundley, 2002). Nevertheless, van Teijlingen and Hundley asserted that individuals who had participated in the preliminary study were not included as the sample of the empirical study. The concern is that inclusion of these participants could lead to potential bias in results due to familiarity with the procedure and survey instrument.

The organization lists were obtained from BI vendors during a business conference and through extensive online search using keywords such as "Malaysia" and "BI tool". Additional search was also conducted by visiting BI vendor websites, press releases, and websites of Malaysian companies to search for the Malaysian organizations that have implemented BI systems and/or BI tools. Based on the lists, individuals were contacted by phone and email to request their consent to participate in the study. Upon receiving their consent, questionnaires were sent to them either personally or through email.

148 Malaysian organizations had been identified as the samples for the survey was carried out in the empirical study. However, there were 52 organizations who agreed to participate in this survey. Majority of the organizations that refused to participate in the survey responded that it is against their company policy to reveal confidential data or information to others even if it is for the use of educational purpose. Despite the small sample size (n= 52), it is deemed sufficient for this research survey as supported by Roscoe's rule of thumb (1975), that is samples are of at least 30 or more

participants. An adequate sample size is required to ensure normality of the data and to provide greater statistical validity of the results so that inferences can be generalized to the population (Hill, 1998; Chung et al., 2005).

3.7 Research Instrument

To evaluate the efficiency of each dimension in the proposed BI maturity model as shown in Figure 2.14 among Malaysian organizations, a structured questionnaire survey approach was used. The survey questionnaire as appended in Appendix A contains two sections: Section A and Section B.

Section A in the questionnaire sought information about the background data of participants and organizations. In Section B, it contained closed-ended questions in which an item was constructed for each component within the four dimensions (i.e. organizational management- 11 items, process- 5 items, technology- 6 items, and outcome- 3 items), with the total of 25 items. A five-point scale which corresponds to the five levels of maturity was used where scale 1 indicates the lowest level (i.e. Initial) and scale 5 indicates the highest level (i.e. Optimizing). Each maturity level consists of certain criteria that need to be fulfilled before an organization moving to next level. The items covered in Section B were created based on the maturity description of all the maturity models and components that have been reviewed in chapter 2. The respondents were instructed to rate their organizations' BI environments by choosing the set of statements that best represent their understanding and perspectives in relation to each of the components within the four dimensions.

Prior to launching the empirical study, the questionnaire was pilot-tested in the preliminary study to validate the content and reliability of the questionnaire. The adoption of content validation approach in this research ensures that the instrument is comprehensive enough to measure the concepts being studied. Five experts in the BI area were engaged to assess logical consistencies and validate conciseness of each question in the questionnaire. Survey instrument was administered face-to-face because more details and explanations can be obtained directly from the experts as well as ambiguous responses can be clarified (Forza, 2002). The comments collected from these experts led to several minor modifications of the wording, length, and item sequence in the questionnaire to reflect their feedback.

In the meantime, a reliability test was carried out using Cronbach's alpha, which measures the internal consistency of the survey questionnaire which consists of 25 items measuring the components built into each dimension. The questionnaire has demonstrated a high level of internal consistency and reliability among items in which the Cronbach's alpha coefficient of the four dimensions ranging from 0.757 to 0.937 as shown in Table 3.1. Since the Cronbach's alpha values for all the four dimensions exceeded the minimum acceptance level of 0.70 as recommended by Hair et al. (2010), thus, the results of Cronbach's analysis show that the questionnaire is well constructed and reliable.

Table 3.1: Cronbach's alpha of the survey instrument

Dimension	Number of items	Cronbach's alpha
Organizational Management	11	0.937
Process	5	0.757
Technology	6	0.765
Outcome	3	0.903

In general, there are multiple factors (e.g. number of items, item intercorrelation, width of the scale, and sample size) that may influence the reliability of the instrument (Cortina, 1993; Spiliotopoulou, 2009).

According to McMillan and Schumacher (2003), the value of Cronbach's alpha is highly dependent on the number of items. Table 3.1 reveals that both process and technology dimensions had lower Cronbach's alpha values (0.757 and 0.765 respectively) compared to other two dimensions. This could be due to the low number of items (i.e. 5 items and 6 items respectively) associated with each dimension (McMillan and Schumacher, 2003). Similarly, it is evident that relatively large number of items (i.e. 11 items) in organizational management dimension may have contributed to the higher Cronbach's alpha value (0.937).

However, the Cronbach's alpha value for the outcome dimension is relatively high although it is derived from 3 items only. It appears that number of items does not affect the Cronbach's alpha value. This high value may be due to high inter-relatedness between items within the reliability test.

3.8 Data Collection Procedure

As noted in section 3.5, the empirical study was then carried out through a quantitative questionnaire-based survey in Malaysia to collect the relevant data. The subjects' consent to participate in the survey was obtained either through phone conversation with the heads of Corporate Communications/Public Relations department or through email prior to their involvement in the empirical study. The email containing letter of invitation (as appended in Appendix B) was sent to all the subjects to inform the purpose of the survey and the expected duration of the subject's participation (i.e. around 20 minutes).

Once the participations were confirmed, the questionnaires were then distributed through email or hand-delivered to the heads of IT department/division or senior managers with BI responsibilities in the selected organizations across a wide range of organizational size. A follow-up reminder email and/or phone call was made to those participants who did not respond within two weeks after the questionnaire was sent out to increase the response rate. From the 148 questionnaires distributed, a total of 52 completed questionnaires were returned. This correlates to a response rate of 35.1 percent.

This research conformed to the ethical standards of the university. A proposal was submitted to and approved by, the university Senate members prior to commencement of the research. The privacy of participants was protected and all questionnaires containing personal information would remain confidential. Participants were assured that the findings would be used for the academic purpose only. All the potential ethical concerns were fully addressed in this research.

3.9 Data Analysis

Data analysis is one of the most important tasks in the entire research process. It involved the coding of data and interpreting the results obtained using SPSS (Statistical Package for Social Science). Both descriptive and inferential statistical analysis methods were used to analyse the data and test the hypotheses formulated in chapter 1.

As mentioned in section 3.7, each dimension (Likert scale item) in BI maturity model is composed of a series of Likert-type items (i.e. organizational management- 11 items, process- 5 items, technology- 6 items, and outcome- 3 items), with a total of 25 items. According to Boone and Boone (2012), data from summated Likert scale are considered as interval although data from individual Likert-type item are treated as ordinal. Therefore, Likert scale items in this research are combined into a single composite variable (mean score), i.e. "BI maturity" and are analyzed at the interval measurement scale. Boone and Boone (2012) also suggested using parametric methods such as means, standard deviations (Std. Dev.), t-test, and ANOVA to analyze interval Likert scale data.

In this research, descriptive statistics were used to find out the participating organizations' demographic data and to provide an initial insight to BI environment of Malaysian organizations. The demographic data consisted of types of industry, organizational size, and the age of BI initiatives. These research findings are presented through the use of tables and figures (e.g. bar and pie charts), which are further described in sections 4.2 and 4.3.

Moreover, descriptive statistics were also used to assess the current maturity level of BI implementation in Malaysian organizations. Means, standard deviation, frequency and percentage of cases were generated to find out the number of participating organizations that rating the maturity level for each component that built into the four dimensions of BI such as organizational management, process, technology and outcome. Then, an average of the rating scores in each dimension was used to determine the current BI maturity level in Malaysian organizations.

Besides, inferential statistics such as independent-samples t-test and one-way ANOVA test were used to test hypotheses 1 (H1), 2 (H2), and 3 (H3).

3.9.1 The Independent-samples T-test

The independent-samples t-test was applied to test the hypothesis 1 (H1), to examine whether the types of industry have significant effects on the BI maturity. According to Zikmund and Babin (2013), t-test is used to compare mean differences between two independent groups. It involves a categorical (nominal or ordinal) independent variable and a continuous (interval or ratio) dependent variable.

Mitchell and Jolley (2013) stated that for t-test to be valid the following two key assumptions must be satisfied: (1) having at least interval scale data and (2) samples must be independent. In this research, H1 involved one independent variable (i.e. types of industry) with two groups (i.e. service and non-service) and one dependent variable (i.e. BI maturity) that is analyzed on an interval scale. Thus, t-test was deemed appropriate to use for comparison of these two groups since the sample data met these two key assumptions. Aside from that, Hinton (2014) also stated that t-test allows the compared groups to have different sample sizes "as long as the different is not too great, and as long as the assumption of equal population variance assumption is still met" (p. 131).

3.9.2 The One-way ANOVA Test

The one-way (or one-factor) ANOVA test was employed to test the hypotheses 2 (H2) and 3 (H3). According to Zikmund and Babin (2013), one-way ANOVA test is considered as an extension of the independent-samples t-test which is concerned with the mean differences of more than two independent groups based on one factor. In other words, it is similar to t-test, using a continuous (interval or ratio) dependent variable and a categorical (nominal or ordinal) independent variable.

Mitchell and Jolley (2013) stated that the results of one-way ANOVA test are considered reliable if the following two key conditions are met: (1) dependent variable must be at least on interval scale and (2) samples are assumed independent to each other. In this research, H2 involved one independent variable (i.e. organizational size) consisting of three groups (i.e. small-, medium-, and large-sized). Likewise, there were one independent variable (i.e. age of BI initiatives) with three groups (i.e. less than 5 years, 5 to 6 years, and more than 6 years) involved in H3. Therefore, one-way ANOVA is the appropriate statistical technique to investigate whether the interval-scaled dependent variable (i.e. BI maturity) differs based on grouping variable since the sample data satisfied the key conditions.

Table 3.2 summarises the statistical methods that were used to test each hypothesis. The results of data analysis are discussed in chapter 4.

Table 3.2: Summary of hypothesis and the statistical method

Hypothesis		Statistical method
H1:	The types of industry have significant effects on the BI maturity.	• Independent-samples t-test
H2:	The organizational size has a significant effect on the BI maturity.	• One-way ANOVA test
H3:	The age of BI initiatives has a significant effect on the BI maturity.	• One-way ANOVA test

3.10 Conclusions

This chapter described the activities and processes involved such as identified the research samples for both preliminary and empirical studies, and identified data analysis methods in order to validate all the research objectives formed in chapter 1. The research methodology explained in this chapter leads to the discussion of research findings in the following chapter.

CHAPTER 4

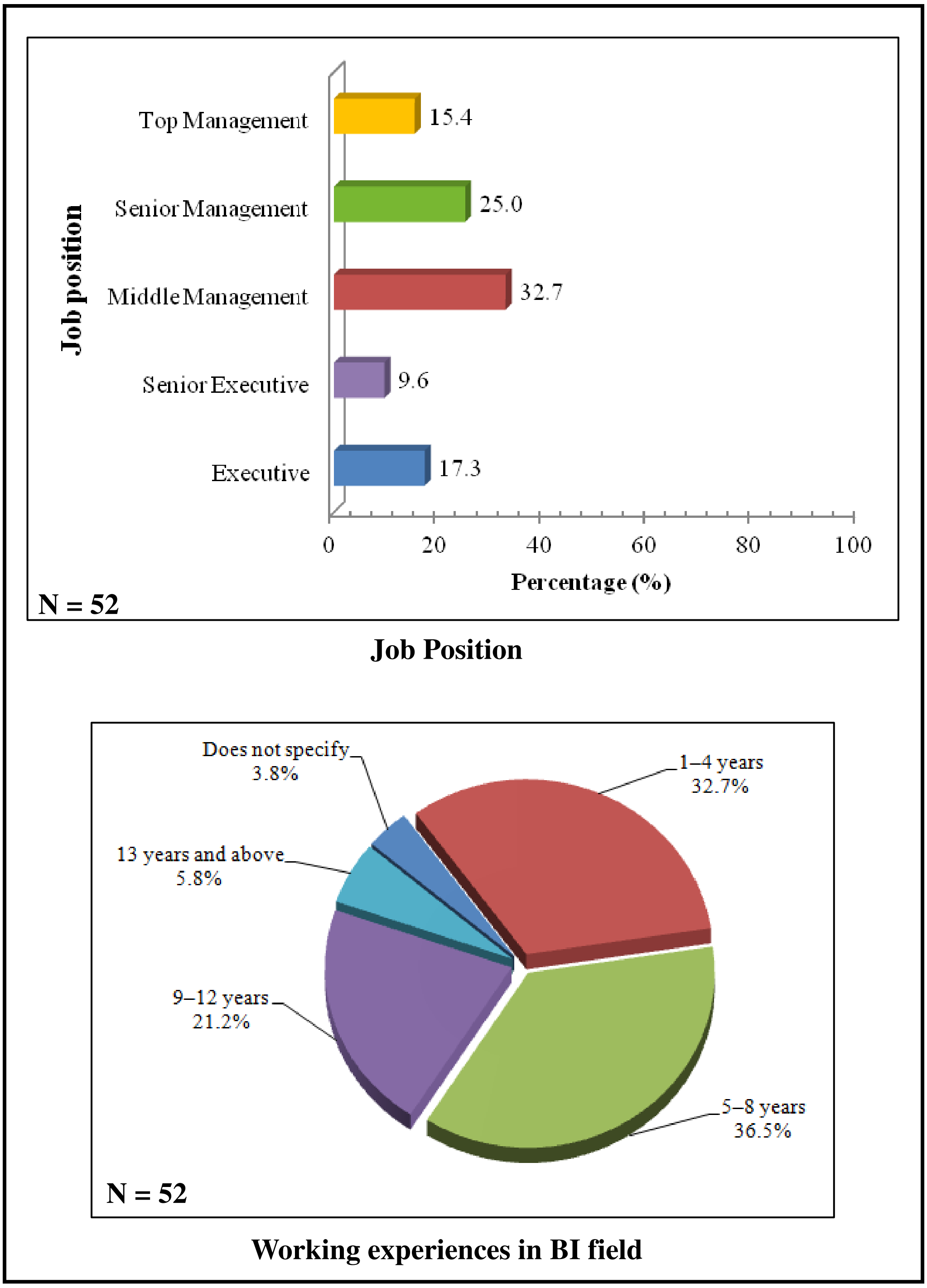
DATA ANALYSIS AND RESEARCH FINDINGS

4.1 Introduction

This chapter presents the research results of data analysis where the data was collected using survey questionnaire. The findings are concerned with the research objectives that were formed at the early stage of the research. Data analysis started with the coding of data and was completed by interpreting the results obtained using SPSS (Statistical Package for Social Science). The discussion of the results of data analysis is divided into three sections as follows:

- The results of data analysis about the demographic data of participating organizations
- The results of data analysis about the BI maturity level in Malaysian organizations
- The results of hypotheses testing

Before presenting the results of data analysis on the above three sections, the summary of the respondents' background data is presented in Figure 4.1.



Job Position

Working experiences in BI field

Figure 4.1: Respondents' background data

In the participating organizations, the participants who responded to this survey ranged from executive to top management level from BI or IT related departments. From the results shown in Figure 4.1, it was found that most of the respondents were from middle management level (e.g. BI/IT manager, assistant BI/IT manager) representing 32.7 percent of all respondents. There were 13 respondents (25 percent) from senior management level (e.g. Head of BI/IT department, senior manager), followed by 9 respondents (17.3 percent) from executive level (e.g. BI analyst, business system analyst), and 8 respondents (15.4 percent) from top management level (e.g. CIO, director, assistant director, vice president). Only 5 respondents (9.6 percent) were from senior executive level (e.g. senior system analyst, senior BI support).

Furthermore, from Figure 4.1, it can be seen that majority of the respondents were experienced and knowledgeable in BI field. Out of 52 respondents, 19 of them (36.5 percent) had 5 to 8 years of BI working experiences, followed by 17 respondents (32.7 percent) with 1 to 4 years experiences, and 11 respondents (21.2 percent) with 9 to 12 years experiences. There were minority (5.8 percent or 3 respondents) reported that they had 13 years and above working experiences in BI field. In addition, there were 2 respondents (3.8 percent) did not specify their length of working experiences in BI field.

4.2 The Results of Data Analysis about the Demographic Data

This section presents the demographic profile of the participating organizations. The demographic data consisted of types of industry, organizational size, types of BI vendor products used, and age of BI initiative.

This research intends to assess whether or not the demographic data of the participating organizations could influence their BI maturity.

4.2.1 Demographic Data: Types of Industry

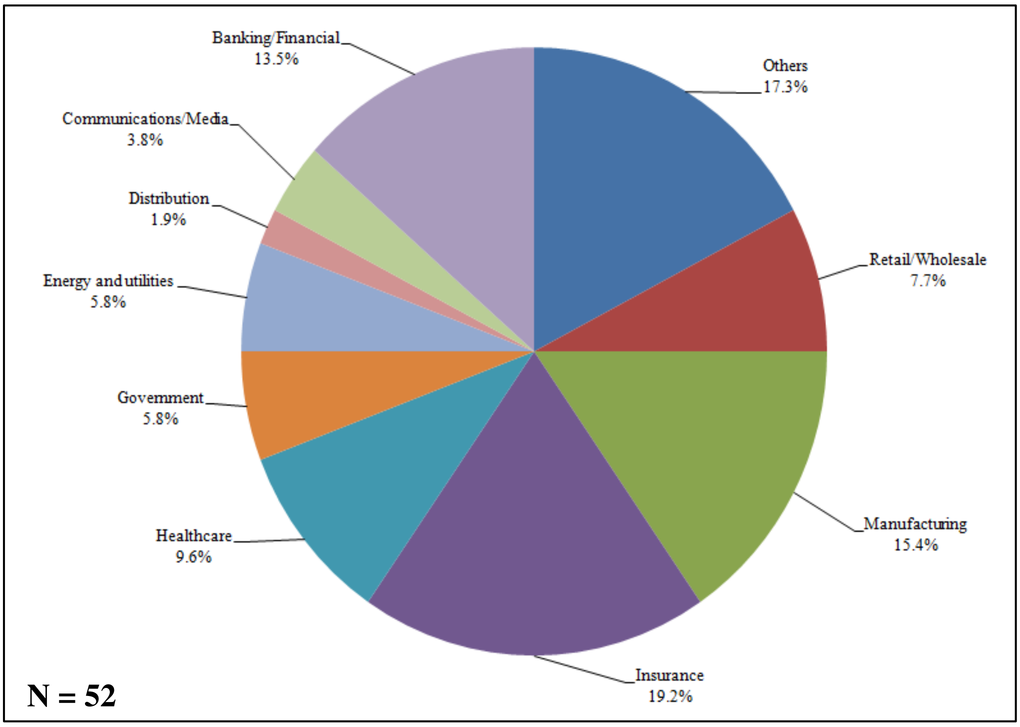


Figure 4.2: Types of industry

A wide variety of industries were represented in this research. The results as revealed in Figure 4.2 show that most of the participating organizations were from insurance industry (19.2 percent). Then, it was followed by 17.3 percent of the organizations from other industries (such as automotive, aviation, sales/marketing, tourism and hospitality, semiconductor, and office automation), 15.4 percent from manufacturing industry, 13.5 percent from banking/financial industry, 9.6 percent from healthcare industry, and 7.7 percent form retail/wholesale industry. Besides, there were 5.8 percent of the organizations from government and energy and utilities industries, respectively, followed by 3.8 percent of organizations were from communications/media industry. Only 1.9 percent of the organizations were from distribution industry.

Table 4.1: Types of industry and number of participating organizations

Types of industry	Number of participating organizations
Service industries:	
Aviation	2
Banking/Financial	7
Communications/Media	2
Energy and utilities	3
Government	3
Healthcare	5
Insurance	8
Sales/Marketing	1
Tourism and hospitality	1
Total	**32**
Non-service industries:	
Automotive	1
Distribution	1
Manufacturing	10
Office Automation	1
Retail/Wholesale	4
Semiconductor	3
Total	**20**

Following the research works of Elbashir et al. (2008) and Raber et al. (2013), the types of industry are then categorized into two groups namely service and non-service industries for analysis purposes. Table 4.1 shows a higher representation from service industries which constitute 32 organizations (61.5 percent) whereas non-service industries comprises of 20 organizations

(38.5 percent).

4.2.2 Demographic Data: Organizational Size of the Participating Organizations

With respect to size of an organization, it was determined by the number of employees in the organization. As can be perceived through Figure 4.3, majority of the organizations (36.5 percent) have 1,001 to 5000 employees, followed by those organizations with 501 to 1000 (17.3 percent) and 5,001 to 10,000 (15.4 percent) employees. Besides, there were 13.5 percent of the organizations that have employees of 1 to 500 and 10,001 to 25,000 respectively. Organizations with 25,001 to 50,000 employees had the lowest response rate with 3.8 percent.

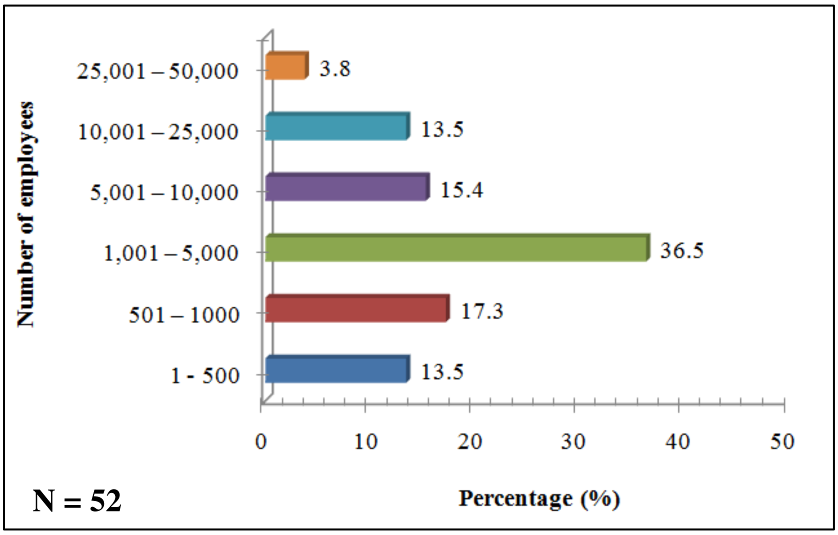


Figure 4.3: Number of employees in the participating organizations

For analysis purposes, the organizational size is classified into small (1-1000), medium (1001-5000), and large (>5000) enterprises, based on the size group classification in Ghosh's study (2011). As shown in Figure 4.4, most of the participating organizations ranged from medium- (36.5 percent) to large-sized enterprises (32.7 percent) with more than 1000 employees. The rest of the participating organizations (30.8 percent) were from small-sized enterprises.

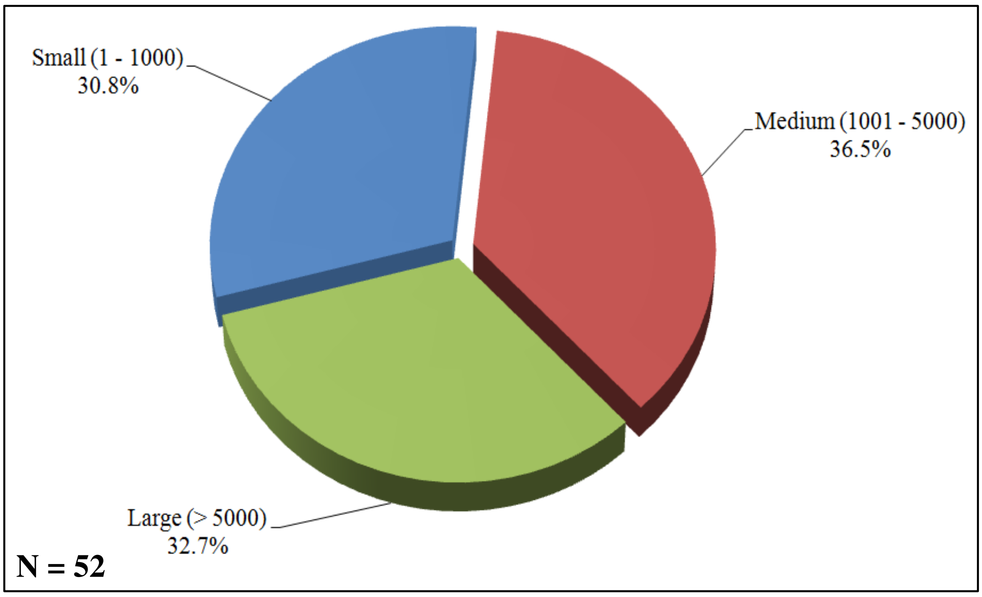


Figure 4.4: Organizational size of the participating organizations

4.2.3 Demographic Data: Types of BI Vendor Products used in the Participating Organizations

The findings in Figure 4.5 show high preferences in SAP (34.6 percent) and SAS (28.8 percent), followed by IBM Cognos (25 percent), Microsoft (15.4 percent), Oracle (13.5 percent), and QlikTech (7.7 percent). Only 8 percent of the organizations used MicroStrategy products. The rest of the participating organizations (23.1 percent) used other BI products such as

ProClarity, Speedminer, Informatica, and Teradata.

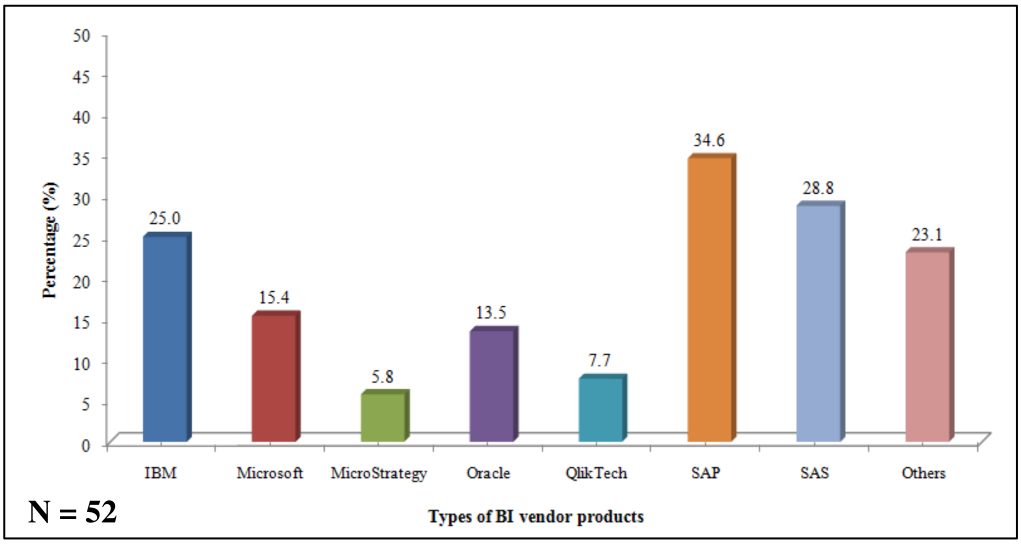


Figure 4.5: Types of BI vendor products in participating organizations

4.2.4 Demographic Data: Age of BI Initiatives in the Participating Organizations

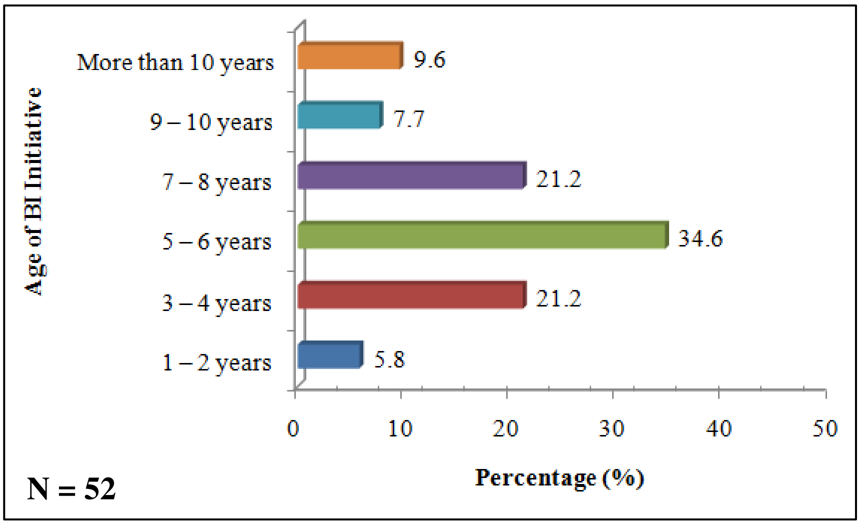


Figure 4.6: Age of BI initiatives in the participating organizations

From Figure 4.6, it can be seen that 18 respondents (34.6 percent) stated that their BI initiatives had been operational for 5 to 6 years. This was followed by organizations with 3 to 4 years experience and 7 to 8 years experience (21.2 percent respectively), more than 10 years (9.6 percent), and 9 to 10 years (7.7 percent). Only 3 respondents (5.8 percent) indicated their organizations have 1 to 2 years experience in using BI.

For analysis purposes, the age of BI initiative was categorized into three groups as shown in Figure 4.7. As revealed in Figure 4.7, there were 38.5 percent of BI initiatives had existed for more than 6 years, followed by 34.6 percent for 5 to 6 years. However, only 26.9 percent of BI initiatives had existed for less than 5 years.

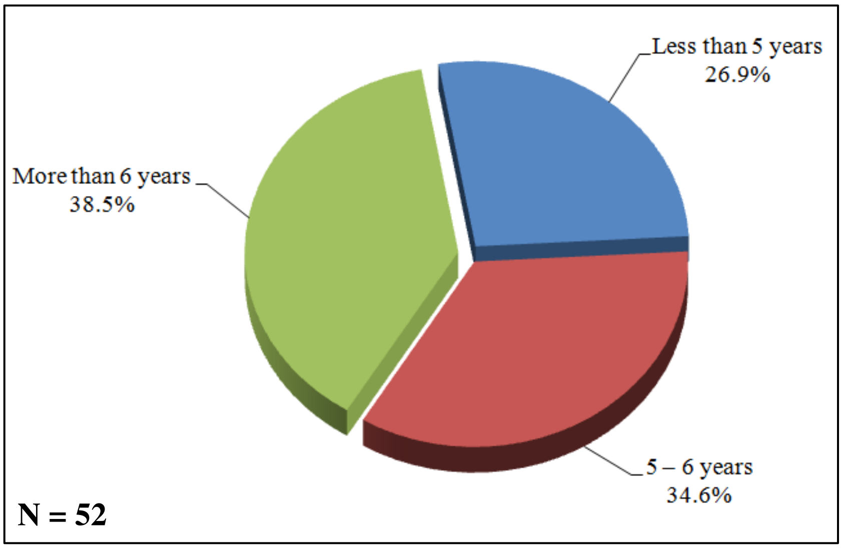


Figure 4.7: Classification of BI age in the participating organizations

4.3 The Results of Data Analysis about the BI Maturity Level in Malaysian Organizations

The respondents were asked about their opinions on the factors that would likely affect BI maturity level of their organizations. Figure 4.8 shows that most of the respondents (88 percent) believed that data quality will affect their organizations' BI maturity level. This was followed by business commitment (75 percent), skills and competencies (71 percent), IT commitment (56 percent), technologies and tools (54 percent), and training (52 percent).

Additionally, 48 percent of respondents indicated that vision, strategy, and goals will also influence BI maturity. Meanwhile, 33 percent of respondents considered change management process as one of the factors and 23 percent of respondents stated sponsorship and funding is also another factor that affects BI maturity. There were 12 percent of respondents added a few other factors such as data governance, organisation culture, expertise availability, data integration, data ownership, information quality, user adaptability, and data usage to support business.

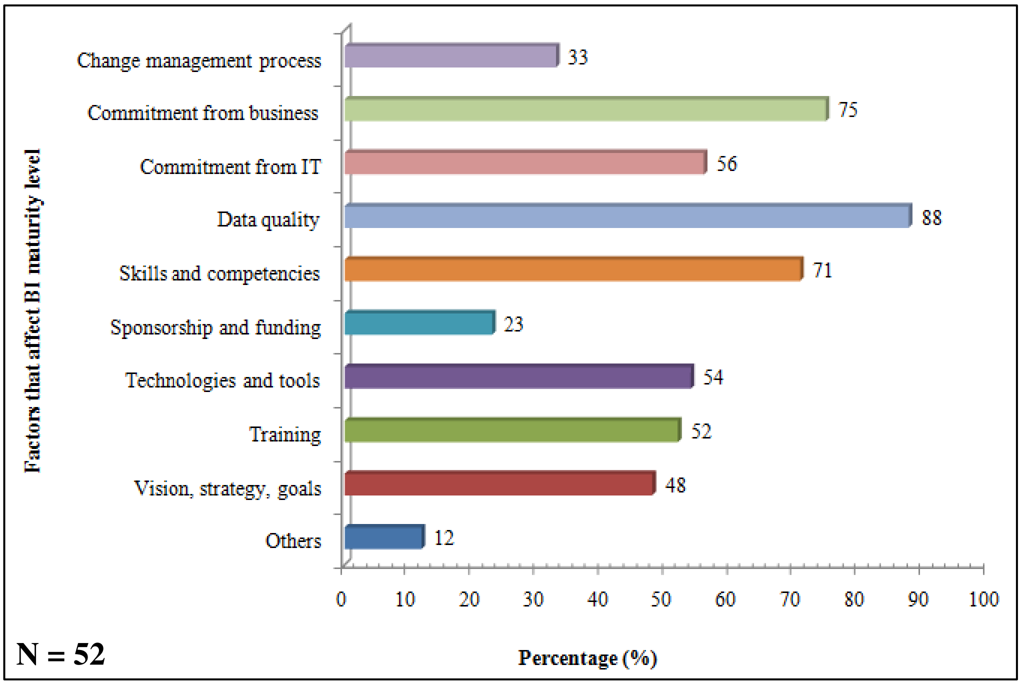


Figure 4.8: Factors that would likely affect BI maturity level in the participating organizations

These findings show that participating organizations' BI maturity tends to be influenced through the combination of various key factors. These influencing factors were denoted as some components and then mapped into four dimensions to compose the BI maturity model as illustrated in Figure 2.14.

The subsequent subsections present the rating results for each of the BI dimensions in the MOBI maturity model as depicted in Table 4.2. The respondents were asked to rate the maturity level of the components in each dimension using a five-point scale which corresponds to the five levels of maturity in which 1 indicates the lowest level (i.e., Initial) and 5 indicates the highest level (i.e., Optimizing).

Table 4.2: Four dimensions with the subcomponents in each dimension

Dimension	Components
Organizational management	Vision, Goals, Scope, BI Awareness, Strategic Alignment, Business Commitment, IT Commitment, Governance, Skills and Competencies, Training, Sponsorship and Funding
Process	Implementation, Change Management, Master Data Management, Metadata Management, Data Governance
Technology	Data Warehousing, Master Data Architecture, Metadata Architecture, ETL, OLAP, Reporting and Analysis
Outcome	Data Quality, Information Quality, KPIs

4.3.1 Organizational Management Dimension

The focus of "Organizational Management" dimension is on how an organization is structured to support BI related business processes. It includes

11 components which are discussed in the following subsections. Table 4.3 and Figure 4.9 show the frequency distribution of maturity level for each component in organizational management dimension.

Table 4.3: Frequency and percentage of maturity level for each component in the organizational management dimension (N = 52)

Component	Maturity level	Frequency	Percentage
Vision	Initial	1	1.9
	Repeatable	5	9.6
	Defined	24	46.2
	Managed	17	32.7
	Optimizing	5	9.6
Goals	Initial	1	1.9
	Repeatable	4	7.7
	Defined	25	48.1
	Managed	17	32.7
	Optimizing	5	9.6
Scope	Initial	3	5.8
	Repeatable	13	25.0
	Defined	15	28.8
	Managed	19	36.5
	Optimizing	2	3.8
BI awareness	Initial	1	1.9
	Repeatable	11	21.2
	Defined	20	38.5
	Managed	16	30.8
	Optimizing	4	7.7
Strategic alignment	Initial	5	9.6
	Repeatable	10	19.2
	Defined	25	48.1
	Managed	6	11.5
	Optimizing	6	11.5

Table 4.3 (Continued)

Component	Maturity level	Frequency	Percentage
Skill and competencies	Initial	0	0
	Repeatable	9	17.3
	Defined	32	61.5
	Managed	9	17.3
	Optimizing	2	3.8
Business commitment	Initial	1	1.9
	Repeatable	14	26.9
	Defined	23	44.2
	Managed	9	17.3
	Optimizing	5	9.6
IT commitment	Initial	0	0
	Repeatable	12	23.1
	Defined	20	38.5
	Managed	10	19.2
	Optimizing	10	19.2
Governance	Initial	7	13.5
	Repeatable	11	21.2
	Defined	21	40.4
	Managed	10	19.2
	Optimizing	3	5.8
Training	Initial	1	1.9
	Repeatable	27	51.9
	Defined	17	32.7
	Managed	7	13.5
	Optimizing	0	0
Sponsorship and funding	Initial	6	11.5
	Repeatable	11	21.2
	Defined	8	15.4
	Managed	5	9.6
	Optimizing	22	42.3

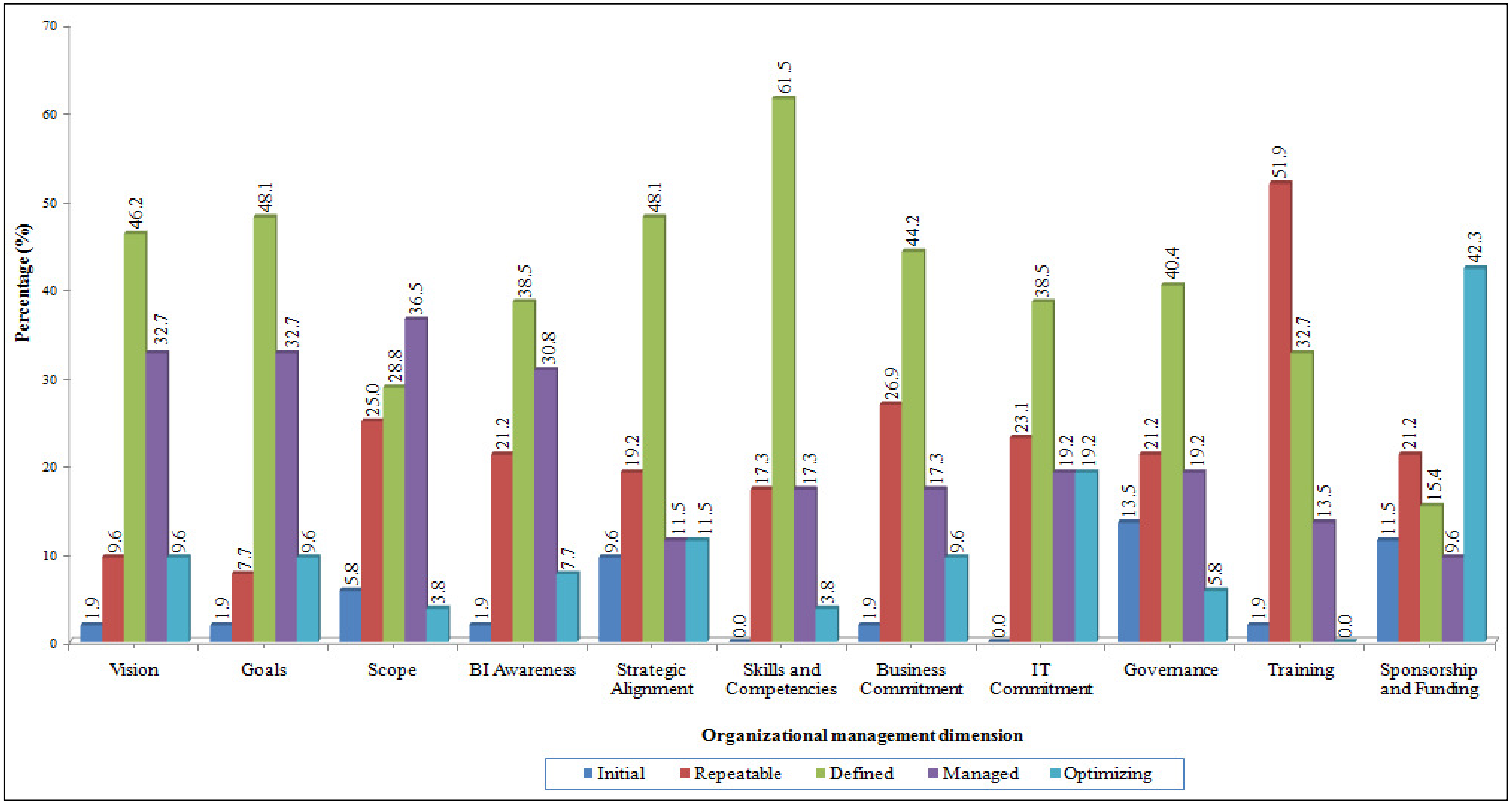


Figure 4.9: Frequency and percentage of maturity level for each component in the organizational management dimension

4.3.1.1 Vision

As can be revealed in Table 4.3 and Figure 4.9, most of the respondents (46.2 percent) stated that they have defined a strategic BI vision and BI is seen as a monitoring system, which is the indicative of level 3 (Defined). Meanwhile, 32.7 percent of respondents rated their BI vision as level 4 (Managed) in which their organizations envisioned BI as a business-critical system for improved organizational performance.

Besides, a small number of respondents rated their BI vision as level 2 (Repeatable) and level 5 (Optimizing) with 9.6 percent respectively. The former viewed BI as an analytical system that support simple analysis tasks while the latter viewed BI as a strategic system that provides a competitive edge driving the market. However, only 1.9 percent of respondents rated level 1 (Initial) for BI vision as his organization did not have a clear BI vision and BI is seen as a mere reporting system.

4.3.1.2 Goal

Different organizations may have different goals in implementing their BI. Based on the results in Table 4.3 and Figure 4.9, almost half of the respondents (48.1 percent) indicated their organizations have defined overall BI goals as to monitor business activities and increase departmental effectiveness, which is the indicative of level 3 (Defined). This was followed by 32.7 percent of respondents graded their organizations' BI goals (i.e., to predict business activities and model results) as level 4 (Managed).

Moreover, there were 9.6 percent of respondents graded BI goals (i.e., move toward self-service environment) as level 5 (Optimizing). The results also show that there were 9.6 percent of respondents that opted for level 2 (Repeatable) in using BI to perform analysis, whereas only 1.9 percent of respondents rated their achievement of BI goals as level 1 (Initial) namely using BI to produce reports and view historical data.

4.3.1.3 Scope

From Table 4.3 and Figure 4.9, most of the respondents (36.5 percent) indicated that their organizations' scope of BI initiatives extend across the enterprise to support important business processes, which is the indicative of level 4 (Managed). This was followed by 28.8 percent of organizations rated level 3 (Defined) where BI initiatives are integrated and used by most or all departments of the organizations. Meanwhile, there were 25 percent of organizations that opted for level 2 (Repeatable) where some departments are using BI but lack of integration between BI initiatives.

Apart from that, there were only a small number of respondents rated level 1 i.e. "Initial" (5.8 percent) and level 5 i.e. "Optimizing" (3.8 percent) for their organizations' scope of BI initiatives. The former indicated BI is used only by individual users while the latter indicated BI coverage is expanded to include suppliers, customers and business partners.

4.3.1.4 BI awareness

The degree of awareness in BI could also affect the BI maturity of an organization. The findings in Table 4.3 and Figure 4.9 reveal that 38.5 percent of the organizations rated level 3 (Defined) for this component where key stakeholders of all departments are aware of BI potentials and have defined BI roadmap for business development. This was followed by 30.8 percent of organizations that rated level 4 (Managed) where they have an enterprise-wise awareness of BI for business improvement. Nevertheless, 21.2 percent of respondents reported that only some departments in their organizations are aware of BI potentials, which is the indicative of level 2 (Repeatable).

Other than that, there were only a small number of organizations (7.7 percent) opted for level 5 (Optimizing) where they are able to improve current and future BI initiatives. In contrast, only 1.9 percent of organizations rated level 1 (Initial), that is, limited awareness of BI potentials.

4.3.1.5 Strategic alignment

As can be seen in Table 4.3 and Figure 4.9, most of the organizations (48.1 percent) opted for level 3 (Defined) where they have defined strategic plans to align BI initiatives with business strategy. This was followed by 19.2 percent of organizations that rated level 2 (Repeatable) where there is no strategic plan in place.

Meanwhile, there were 11.5 percent of organizations rated level 4 (Managed) and level 5 (Optimizing) respectively. The former indicated that alignment model is in place while the latter indicated that continuous modification is done in alignment model so that BI strategy is adaptable to new business initiatives. However, only 9.6 percent of organizations rated level 1 (Initial) where their BI initiatives were only aligned with IT strategy.

4.3.1.6 Skills and competencies

The findings in Table 4.3 and Figure 4.9 show that more than half of the organizations (61.5 percent) rated level 3 (Defined) for this component in which most of the necessary BI skills and competencies are in place for running BI initiatives. Only a small number of organizations opted for level 2 i.e. “Repeatable” and level 4 i.e. “Managed” (17.3 percent respectively). The former have established basic BI skills and competencies for data analysis only while the latter have established new, highly-demand skills and competencies for upcoming BI initiatives.

However, there were only 3.8 percent of organizations have all necessary BI skills and competencies in place to support continual improvement. None of the organizations rated level 1 i.e. “Initial” for this component.

4.3.1.7 Business commitment

As can be perceived through Table 4.3 and Figure 4.9, majority of the respondents (44.2 percent) rated their organizations' business commitment as level 3 (Defined) where some critical BI initiatives were being driven by business people. This was followed by 26.9 percent of respondents reported that their organizations' BI have started to shift to business driven although BI is still viewed as an IT-driven initiative, which is the indicative of level 2 (Repeatable). Besides, there were 17.3 percent of respondents that rated level 4 (Managed) for this component which indicated that business people are actively involved in most of the BI initiatives. Only 1.9 percent of respondents indicated their organizations had the lowest business commitment (level 1 i.e. Initial) where business people do not involved in BI projects.

4.3.1.8 IT commitment

As can be seen in Table 4.3 and Figure 4.9, it was found that 38.5 percent of respondents rated IT commitment as level 3 (Defined) where IT people in their organizations have more defined commitment toward BI initiatives. On the contrary, 23.1 percent of respondents reported that their organizations' IT people only commit individual BI projects only, which is the indicative of level 2 (Repeatable). Only 19.2 percent of organizations rated a higher level of IT commitment (level 4 i.e. "Managed" and level 5 i.e. "Optimizing" respectively) where IT people have strong commitment towards BI supports and equal roles as business people in defining business strategy.

None of the organizations rated level 1 i.e. “Initial” for this component.

4.3.1.9 Governance

From Table 4.3 and Figure 4.9, there were 40.4 percents of organizations rated their achievement of the governance component as level 3 i.e. “Defined” where they authorized a cross-departmental team to make some BI-related decisions. Then, it is followed by organizations that rated level 2 i.e. “Repeatable” (21.2 percent) and level 4 i.e. “Managed” (19.2 percent) for BI governance. The former formed some ad-hoc groups to oversee BI activities yet there is lack of authority for decision making, whereas the latter formed a BI steering committee which has enterprise-wide authority for all decisions. Besides, there were 13.5 percent of organizations rated level 1 (Initial) because there is no official authority exists for BI governance. Only a small number of organizations (5.8 percent) achieved level 5 (Optimizing) where their BI governance framework is institutionalized to control decision-making.

4.3.1.10 Training

The findings in Table 4.3 and Figure 4.9 reveal that more than half of the organizations (51.9 percent) rated level 2 (Repeatable) for this component where they provided basic BI tool training only in an ad-hoc basis. This was followed by 32.7 percent of organizations that noted their achievement in level 3 (Defined) where they provided advanced BI tool training for each group of

BI users in a regular basis. Furthermore, there were 13.5 percent of organizations coordinated scheduled and on-going BI training plans for upcoming BI projects, which is the indicative of level 4 (Managed). Only 1.9 percent of organizations rated level 1 (Initial) for this component because they did not have formal BI training plan in plan. None of the organizations achieved level 5 (Optimizing) for training component.

4.3.1.11 Sponsorship and funding

From Table 4.3 and Figure 4.9, majority of the organizations (42.3 percent) achieved level 5 (Optimizing) where all BI initiatives were supported by executive management level (e.g. CEO and other C-level executives). This was followed by 21.2 percent of organizations that rated level 2 (Repeatable) where BI projects were supported separately by departmental management. In addition, there were 15.4 percent of organizations opted for level 3 (Defined) where BI projects were supported by middle management level. Only a small number of organizations rated level 1 i.e. “Initial” (11.5 percent) and level 4 i.e. “Managed” (9.6 percent) for this component. The former did not have sponsorship and specific budget for BI projects while the latter attained supports from a cross-functional steering committee.

4.3.1.12 Summary of the findings on organizational management dimension

Overall, the findings depicted in Table 4.3 and Figure 4.9 show that majority of the participating organizations achieved level 3 (Defined) for most of the components in organizational management dimension, except scope (level 4 i.e. “Managed”), training (level 2 i.e. “Repeatable”), and sponsorship and funding (level 5 i.e. “Optimizing”) components. Table 4.4 depicts the average mean scores for each component in organizational management dimension.

Table 4.4: Descriptive analysis for organizational management dimension and the maturity level

Component	Mean	Std. Dev.
Vision	3.38	0.87
Goals	3.40	0.85
Scope	3.08	1.01
BI awareness	3.21	0.94
Strategic alignment	2.96	1.08
Skill and competencies	3.08	0.71
Business commitment	3.06	0.96
IT commitment	3.35	1.05
Governance	2.83	1.08
Training	2.58	0.75
Sponsorship and funding	3.50	1.50

As can be seen through Table 4.4, the sponsorship and funding component attained the highest average mean score (3.50). This implies that the organizations surveyed have adequate funding and higher level executive sponsorship engaged in the BI initiatives to ensure long term success of BI initiatives.

Then, this was followed by the goals component with average mean score of 3.40 and vision component with average mean score of 3.38. The findings show that organizations surveyed have achieved these two components quite well where they have established a shared BI vision and company-wide goals that direct the nature and scope of BI initiatives so that desired outcome is achieved. The IT commitment component was ranked at the fourth place in the overall scoring with average mean score of 3.35, while business commitment component was ranked at seventh with average mean score of 3.06. This implies that there is still lack of close partnership between business and IT. The reason could be due to the absence of clear communication and coordination between business and IT stakeholders.

Following that was the BI awareness component with average mean score of 3.21. Despite the increasing awareness of BI potentials, many organizations still view BI as an IT-driven initiative instead of a business initiative. This low level of awareness could lead to the emergence of implementation issues that further impact on outcome of BI initiatives. With regard to scope and the skills and competencies, both components had attained same average mean score i.e. 3.08. This indicates that there are still a limited number of BI users (mainly used by managers and executives) as well as lack of BI skill sets and competencies among non-technical business users. This means that the organizations do not provide a strong platform to enhance and develop BI skill sets and competencies for the users.

On the other hand, the strategic alignment component had average mean score of 2.96. This could be due to the failure to connect BI strategy with the organizational vision and goals. BI strategy should be developed, adapted, and updated continuously. Similarly, governance component had lower average mean score of 2.83. Possible reasons contributed to low degree of governance are ineffective management of cultural change and lack of executive management buy-in to enforce mandates.

Lastly, the training component had the lowest average mean score (2.58). This could be due to the absence of BI specific training policies. Training is an important activity that is often overlooked by organizations. Past studies (e.g. Negash, 2004; Eckerson, 2008) stated that tailored training is a major contributor to high levels of BI usage by increasing the BI users' skills in using the BI tools and available data for analysis. Therefore, training should be provided to users on a regular basis to meet new skills and keep up with changes.

4.3.2 Process Dimension

The "Process" dimension measures the extent to which activities of coordinating and managing BI environment are being carried out successfully. There are five components in this dimension. Table 4.5 and Figure 4.10 show the frequency distribution of maturity level for each component in the process dimension.

Table 4.5: Frequency and percentage of maturity level for each component in the process dimension (N = 52)

Component	Maturity level	Frequency	Percentage
Implementation	Initial	2	3.8
	Repeatable	10	19.2
	Defined	28	53.8
	Managed	8	15.4
	Optimizing	4	7.7
Change management	Initial	7	13.5
	Repeatable	10	19.2
	Defined	25	48.1
	Managed	8	15.4
	Optimizing	2	3.8
Master data management	Initial	3	5.8
	Repeatable	13	25
	Defined	22	42.3
	Managed	10	19.2
	Optimizing	4	7.7
Metadata management	Initial	10	19.2
	Repeatable	2	3.8
	Defined	22	42.3
	Managed	13	25.0
	Optimizing	5	9.6
Data governance	Initial	3	5.8
	Repeatable	8	15.4
	Defined	21	40.4
	Managed	15	28.8
	Optimizing	5	9.6

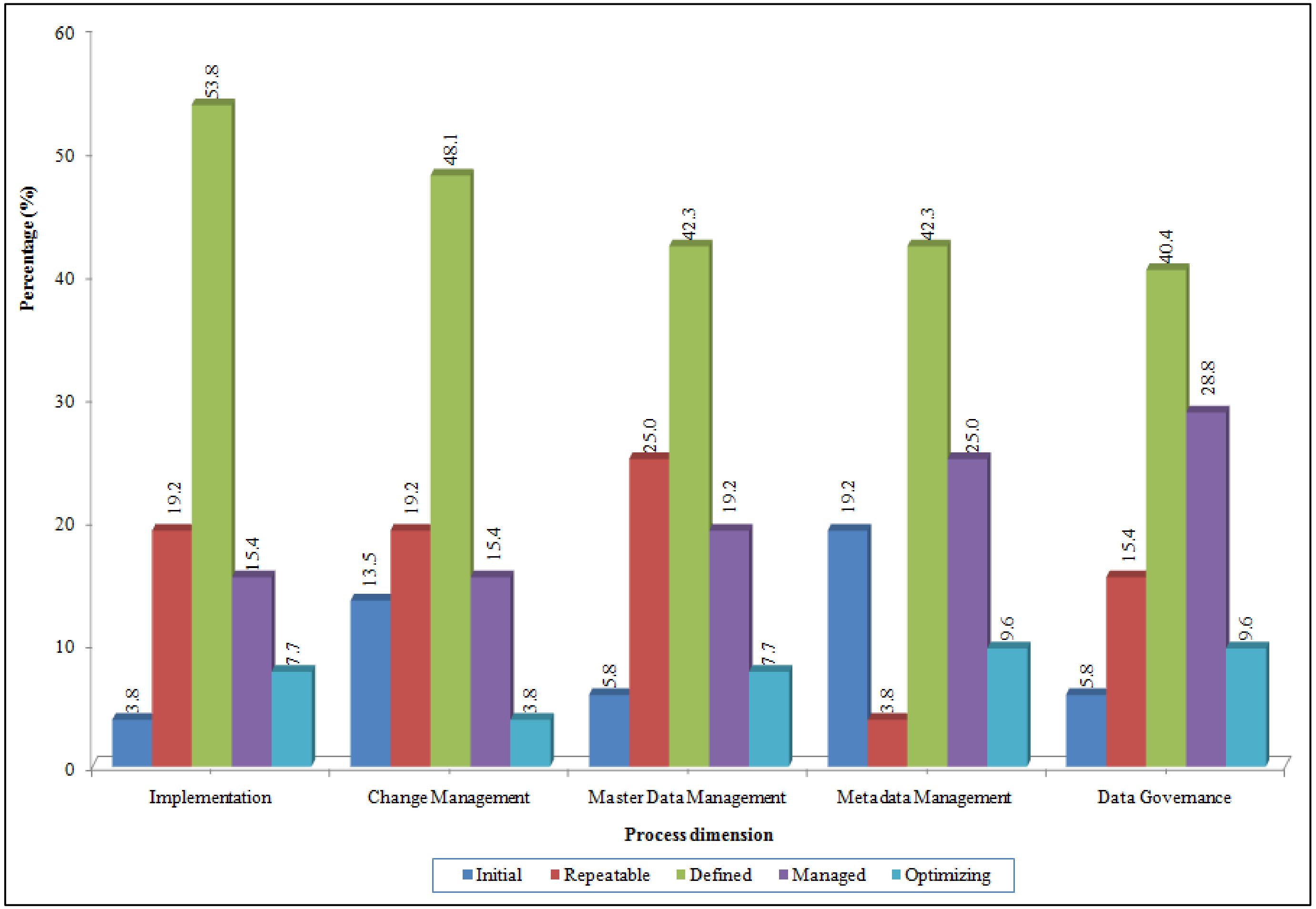


Figure 4.10: Frequency and percentage of maturity level for each component in the process dimension

4.3.2.1 Implementation

From Table 4.5 and Figure 4.10, it was found that more than half of the respondents (53.8 percent) reported that their organizations took phased approach to implement BI modules sequentially with different phases, which is the indicative of level 3 (Defined). This was followed by 19.2 percent of respondents that rated level 2 (Repeatable) where several BI modules were implemented across their organizations at the same time. In addition, there were 15.4 percent of respondents rated level 4 (Managed) and 7.7 percent of respondents rated level 5 (Optimizing). The former reported that they adopted incremental delivery approach while the latter reported that they adopted agile approach to implement BI. Only 3.8 percent of respondents rated level 1 (Initial) where all BI modules were implemented across their organizations at the same time.

4.3.2.2 Change management

From the findings shown in Table 4.5 and Figure 4.10, almost half of the organizations (48.1 percent) opted for level 3 (Defined) where they established a structured change management process and documented standard procedure for handling changes. This was followed by 19.2 percent of organizations that rated level 2 (Repeatable) and 15.4 percents rated level 5 (Managed). The former applied change management process inconsistently in isolated BI projects while the latter applied enterprise-wide change management process on every new project or change. Besides, there were 13.5

percent of organizations that rated level 1 (Initial) namely solved BI change requests in an ad-hoc manner and without following correct processes. Only a small number of organizations (3.8 percent) rated level 5 (Optimizing) where trend analysis and statics about change occurrence and success rate were provided.

4.3.2.3 Master data management

As can be perceived through Table 4.5 and Figure 4.10, 42.3 percent of the organizations rated level 3 (Defined) for this master data management component. Specifically, they have defined a set of master data management processes that centralized master reference data and business data rules. This was followed by 25.0 percent of organizations that rated level 2 (Repeatable) where they do not have proper processes to resolve the master data problems. On the other hand, there were 19.2 percent of organizations implemented service-oriented architecture (SOA) to integrate common business methods and data across multiple applications, which is the indicative of level 4 (Managed).

Furthermore, 7.7 percent of organizations rated level 5 (Optimizing) have fully integrated master data management in their business processes to allow transparent access to master data across the organizations. Only 5.8 percent of organizations ranked level 1 (Initial) where they handled master data conflicts, deletions, and changes manually.

4.3.2.4 Metadata management

From Table 4.5 and Figure 4.10, there were 42.3 percent of organizations rated level 3 (Defined) for this component where metadata are managed in one or more metadata repository. Then, it was followed by organizations that rated level 4 i.e. “Managed” (25.0 percent) and level 1 “Initial” (19.2 percent). The former had a centralized metadata repository that standardizes metadata across different sources for users to access, whereas the latter indicated that there is no metadata available for users to view.

Besides, there were 9.6 percent of organizations that rated level 5 (Optimizing) for the metadata management component, where they deployed a web-based centralized metadata repository for users to access up-to-date metadata anytime and anywhere. Only a small number of organizations (3.8 percent) achieved level 2 (Repeatable) where users can only view metadata periodically through metadata reports which are not integrated.

4.3.2.5 Data governance

As can be observed from Table 4.5 and Figure 4.10, most of the organizations (40.4 percent) stated that they have set up data government team and standardized data stewardship activities, which is the indicative of level 3 (Defined). Meanwhile, 28.8 percent of organizations rated their data governance as level 4 (Managed) in which their organizations established an executive-level data governance committee to oversee stewardship activities across the organizations.

On the other hand, there were 15.4 percent of organizations rated level 2 (Repeatable) where they implemented a local data governance program but had not standardized data stewardship activities. Only 9.6 percent of organizations rated level 4 (Optimizing) where they had automated the process of monitoring and enforcement of data governance.

4.3.2.6 Summary of the findings on process dimension

In summary, the findings reported in Table 4.5 and Figure 4.10 show that majority of the participating organizations rated level 3 (Defined) for all the components in process dimension. Table 4.6 presents the average mean scores for each component in process dimension.

Table 4.6: Descriptive analysis for process dimension and the maturity level

Component	Mean	Std. Dev.
Implementation	3.04	0.91
Change management	2.77	1.00
Master data management	2.98	1.00
Metadata management	3.02	1.21
Data governance	3.21	1.02

From Table 4.6, it can be seen that the data governance component attained the highest average mean score (3.21). This indicates that business people aware of the importance of defining policies in every core business processes to enforce accountability for the data consumed and produced.

However, data governance remains immature for some organizations. Possible reason for this result is that the data governance is still viewed as IT responsibility with minimal business involvement and no executive-level support. Expanding data governance program to enterprise-wide requires strong executive commitment and persistence from business leadership on continuous quality and process improvement (Panian, 2010; Goetz, 2013).

Then, this was followed by the implementation component with average mean score of 3.04. This moderate result signifies that organizations with lower maturity rating underestimated the complexity of BI implementation. As BI is iterative and business users expect constant delivery of values, organizations must be agile and rapid in BI implementation so as to quickly adapt to the changing business environment as well as user demand for changes and enhancements (Rehani, 2011). This can be achieved by taking an evolutionary (i.e. iterative and incremental) approach for BI implementation. Therefore, when roll out new BI initiatives, it is imperative to break the deliverables into smaller manageable releases and work in short iteration cycles instead of the “big bang” of the traditional waterfall approach.

Next, the metadata management component was ranked at the third place in the overall scoring with average mean score of 3.02. This moderate result implies that documentation of metadata and reference data has been a common practice in most of the organizations. Yet, some organizations are still lacking of integration and standardization of metadata as well as awareness about the importance of metadata. This may contribute to the use of divergent software tools and repositories with different data models and representation formats, hinders centralization of metadata management. Advancing to a mature metadata management requires an application programming interface (API) and XML (a common interchange format) for users to access metadata via a central metadata repository (Auth and von Maur, 2002).

Furthermore, the master data management component was ranked at the fourth place with average mean score of 2.98. This result reveals that master data management practices are still at early maturity phase. Specifically, definitions for master data management processes (e.g. data creation, maintenance, and usage) are still unclear and integrations between applications are poorly implemented. For organizations to evolve towards an enterprise-wide master data management, it is needed to have strong executive support and a set of master data integration services for propagating master data changes between applications (White, 2007; Silvola et al., 2011).

Lastly, the change management component had the lowest average mean score of 2.77. This reflects that more than half of the organizations possess a positive attitude towards change. However, small fraction of organizations (13.5 percent) is still applying change management approach locally to particular BI initiatives or in an ad-hoc manner. This may be due to ineffective change leadership, poor communication between stakeholders, and differences in corporate cultures regarding change (Williams and Williams, 2004; Ramanigopal et al., 2012). As BI initiatives mature, organizations need to evolve towards an automated enterprise-wide change management process to reflect current business needs.

4.3.3 Technology Dimension

The "Technology" dimension examines the organizational maturity in using various BI tools and architectures. It contains six components which are discussed in the following subsections. Table 4.7 and Figure 4.11 show the frequency distribution of maturity level for each component in the technology dimension.

Table 4.7: Frequency and percentage of maturity level for each component in technology dimension (N = 52)

Component	Maturity level	Frequency	Percentage
Data warehousing	Initial	0	0
	Repeatable	7	13.5
	Defined	16	30.8
	Managed	27	51.9
	Optimizing	2	3.8
Master data architecture	Initial	5	9.6
	Repeatable	11	21.2
	Defined	20	38.5
	Managed	11	21.2
	Optimizing	5	9.6
Metadata architecture	Initial	6	11.5
	Repeatable	10	19.2
	Defined	24	46.2
	Managed	10	19.2
	Optimizing	2	3.8

Table 4.7 (Continued)

Component	Maturity level	Frequency	Percentage
ETL	Initial	1	1.9
	Repeatable	3	5.8
	Defined	19	36.5
	Managed	22	42.3
	Optimizing	7	13.5
OLAP	Initial	3	5.8
	Repeatable	5	9.6
	Defined	17	32.7
	Managed	24	46.2
	Optimizing	3	5.8
Reporting and analysis	Initial	3	5.8
	Repeatable	3	5.8
	Defined	30	57.7
	Managed	10	19.2
	Optimizing	6	11.5

4.3.3.1 Data warehousing

As can be observed from Table 4.7 and Figure 4.11, more than half of the respondents (51.9 percent) stated that their organizations had implemented a centralized enterprise data warehouse to support enterprise-wide needs, which is the indicative of level 4 (Managed). Meanwhile, 30.8 percent of respondents placed themselves at level 3 (Defined) in which their organizations had several data warehouses to support cross-departmental needs.

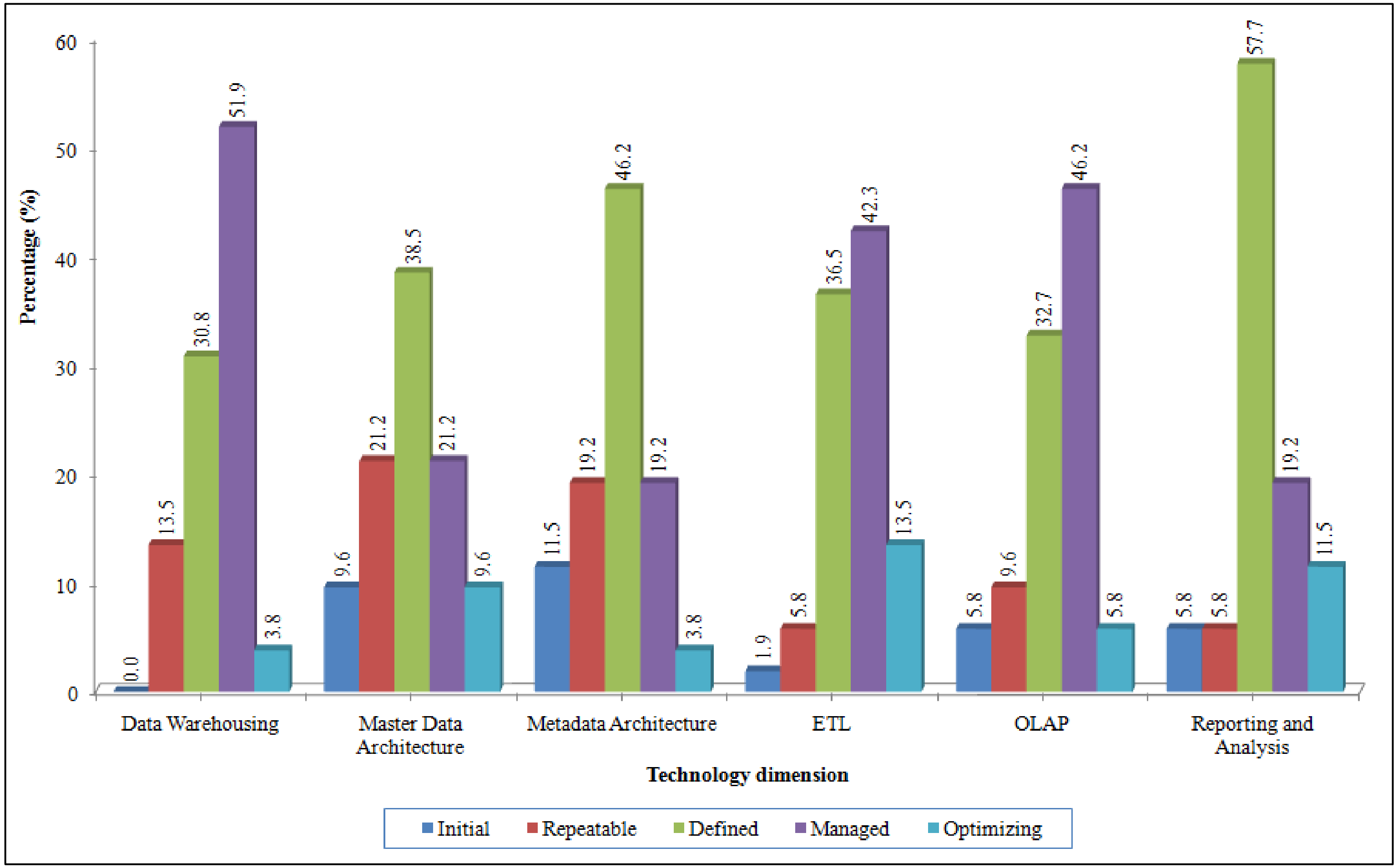


Figure 4.11: Frequency and percentage of maturity level for each component in the technology dimension

Furthermore, there were 13.5 percent of respondents rated level 2 (Repeatable) for the data warehousing component as their organizations stored data in multiple data marts which support departmental needs only. Only a small number of respondents (3.8 percent) rated level 5 (Optimizing) whose organizations used BI services as a data source for users to perform data analysis and access in real time. None of the respondents rated level 1 (Initial) which involves the use of spreadsheets or desktop databases.

4.3.3.2 Master data architecture

The findings in Table 4.7 and Table 4.11 reveal that 38.5 percent of respondents rated level 3 (Defined) in which their organizations had defined master data models for specific business functions and standardized master data architecture for most of the systems. This was followed by 21.2 percent of respondents rated level 2 (Repeatable) and level 4 (Managed) respectively. The former stated that they created master data model for individual business applications only and there was no standardized master data architecture. In contrast, the latter said that core master data model had been defined at enterprise level and all systems comply with master data architecture.

Apart from that, only a small number of respondents rated level 1 i.e. “Initial” and level 5 i.e. “Optimizing” (9.6 percent respectively) for this component. The former indicated that their organizations did not have formal master data architecture and master data model in place. Whereas the latter reported that their organizations focused on continually improved master data architecture and master data models.

4.3.3.3 Metadata architecture

From Table 4.7 and Table 4.11, most of the respondents (46.2 percent) rated level 3 (Defined) in which business metadata were being addressed and business rules were managed in its own application layer. This was followed by 19.2 percent of respondents rated level 2 (Repeatable) and level 4 (Managed) respectively. The former indicated that their organizations managed technical and operational metadata only, and some business rules were isolated in an application layer. Whereas the latter reported that their organizations managed metadata from outside as well and changes to business rules were managed by business managers through user interface.

Besides, the findings in Table 4.7 and Table 4.11 show that there were 11.5 percent of respondents opted for level 1 (Initial) where their organizations had not defined metadata architecture, and business rules were implemented in the program code or application database. Only 3.8 percent of respondents rated level 5 (Optimizing) for this component where changes of business rules were done by a business process.

4.3.3.4 ETL (Extract-Transform-Load)

As can be perceived through Table 4.7 and Figure 4.11, majority of the respondents (42.3 percent) ranked their ETL tools somewhat mature, that is, at level 4 (Managed). Specifically, most of the business areas in their organizations adopted ETL tools with standard functionalities (such as reusable objects and platform independence). This was followed by 36.5 percent of respondents opted for level 3 (Defined) which indicated that their organizations used some of the common ETL capabilities. There were 13.5 percent of respondents rated this component as level 5 (Optimizing) where all ETL tools included all standard functionalities.

Besides, a small number of respondents (5.8 percent) stated that their organizations utilized basic ETL capabilities only, which is indicative of level 2 (Repeatable). Only 1.9 percent of respondents rated level 1 (Initial) for this component as their organizations had not utilized ETL capabilities for data integration.

4.3.3.5 OLAP (Online Analytical Processing)

The findings in Table 4.7 and Figure 4.11 reveal that majority of the respondents (46.2 percent) rated level 4 (Managed) for this component where their OLAP solutions were able to perform most of the analysis and maintenance tasks automatically. This was followed by 32.7 percent of respondents that rated level 3 (Defined) in which OLAP solutions were standardized and several data sources were integrated for analysis. There were 9.6 percent of respondents reported that their OLAP solutions can automate simple maintenance tasks only and there was no integration between data sources for analysis, which is the indicative of level 2 (Repeatable).

In addition, only a small number of respondents rated their organization’s BI maturity at level 1 (Initial) and level 5 (Optimizing) with 5.8 percent respectively. The former stated that their organizations had not defined OLAP technology while the latter indicated that their organizations had implemented OLAP solutions which provide full automation for all daily maintenance tasks.

4.3.3.6 Reporting and analysis

As can be seen in Table 4.7 and Figure 4.11, it was found that more than half of the respondents (57.7 percent) placed themselves at level 3 (Defined) where they implemented data visualization techniques such as dashboards and scorecard to track business performance. This was followed by 19.2 percent of respondents that marked level 4 (Managed) in which predictive analytics were used in their organizations. Furthermore, 11.5 percent of respondents indicated that real-time analytics were used, which is the indicative of level 5 (Optimizing).

Then, the rest of the respondents rated their organizations’ BI maturity at level 1 (Initial) and level 2 (Repeatable) with 5.8 percent respectively. The former said that they relied heavily on static reports and spreadsheets while the latter indicated that they used more interactive reporting tools to perform data analysis.

4.3.3.7 Summary of the findings on technology dimension

From the findings reported in Table 4.7 and Figure 4.11, it can be concluded that majority of the participating organizations rated the maturity level for the components in the technology dimension between level 3 (Defined) and level 4 (Managed). Those components that achieved level 3 are master data architecture, metadata architecture, and reporting and analysis components, whereas data warehousing, ETL, and OLAP were rated at level 4. Table 4.8 reveals the mean scores for each component in technology dimension.

Table 4.8: Descriptive analysis for technology dimension and the maturity level

Component	Mean	Std. Dev.
Data warehousing	3.46	0.78
Master data architecture	3.00	1.10
Metadata architecture	2.85	1.00
ETL	3.60	0.87
OLAP	3.37	0.95
Reporting and analysis	3.25	0.95

As shown in Table 4.8, it can be seen that the ETL component attained the highest average mean score (3.60). ETL tools are somewhat mature in most of the organizations as they have included advanced ETL capabilities required by BI initiatives. It was followed by the data warehousing component with average mean score of 3.46. Despite the high degree of data warehousing, many organizations still keep data in multiple data warehouses without having a centralized data warehouse. This implies that some departments within these organizations still have high degrees of local control over their data structures.

Then, the OLAP component was ranked at third place in the overall scoring with average mean score of 3.37.

Following that was the reporting and analysis component with average mean score of 3.25. This implies that most of the organizations have realized the benefits of data visualization tools and analytics in providing deeper insights into business needs and to predict outcomes. With regard to the master data architecture component, it had attained average mean score of 3.00. This reflects that BI efforts toward master data management are still rudiment. Evolving toward enterprise master data management is a significant effort for many organizations as it requires the maintenance of central master data hub and usage of real-time integration services to propagate the master data to other systems.

Lastly, the metadata architecture component had the lowest average mean score (2.85). This may be due to the limitations of the tools and functionality to capture metadata, hence distributed metadata architecture is used in most of the organizations.

4.3.4 Outcome Dimension

The "Outcome" dimension measures the results of implementing different BI components (e.g. people, processes, tools and architectures). This dimension consists of three components which are discussed in the following subsections. Table 4.9 and Figure 4.12 show the frequency distribution of maturity level for each component in outcome dimension.

Table 4.9: Frequency and percentage of maturity level for each component in outcome dimension (N = 52)

Component	Maturity level	Frequency	Percentage
Data quality	Initial	0	0
	Repeatable	8	15.4
	Defined	30	57.7
	Managed	13	25.0
	Optimizing	1	1.9
Information quality	Initial	1	1.9
	Repeatable	5	9.6
	Defined	23	44.2
	Managed	21	40.4
	Optimizing	2	3.8
KPIs	Initial	2	3.8
	Repeatable	6	11.5
	Defined	23	44.2
	Managed	18	34.6
	Optimizing	3	5.8

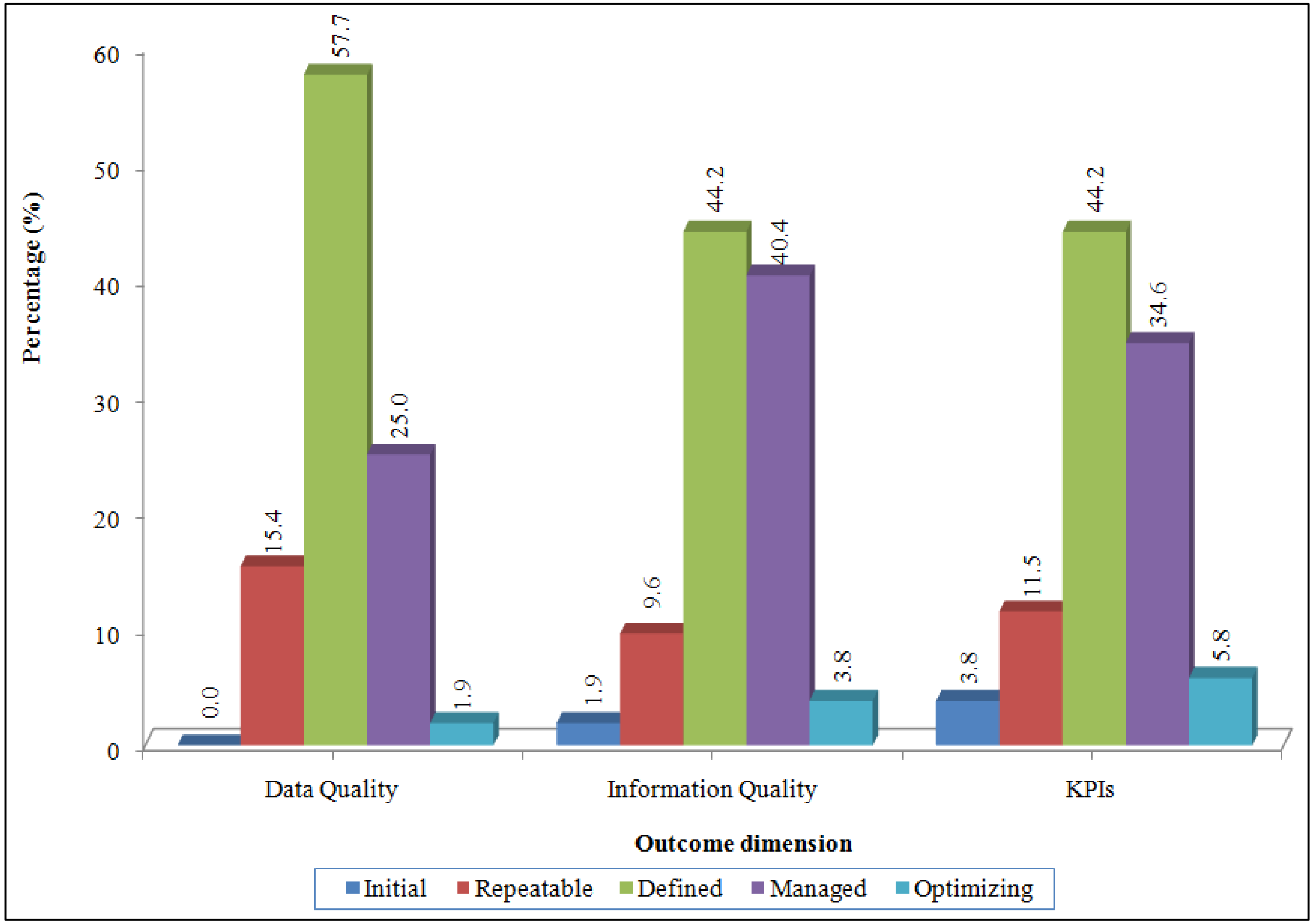


Figure 4.12: Frequency and percentage of maturity level for each component in the outcome dimension

4.3.4.1 Data Quality

As can be seen in Table 4.9 and Figure 4.12, more than half of the organizations (57.7 percent) rated level 3 (Defined) for this component where root cause of data quality issues had been resolved and data are integrated and shared for critical business areas. This was followed by 25 percent of organizations being achieved at level 4 (Managed) as they had incorporated data validation to prevent data defects from occurring. Next, 15.4 percent of organizations were found in level 2 (Repeatable) where they repeated data cleanup due to failure to address root cause of data defects.

There were only 1.9 percent of organizations rated the highest maturity level i.e., level 5 (Optimizing) where their data had achieved all aspects of quality dimensions. None of the organizations rated level 1 (Initial) where data are incorrect, incomplete, and unreliable.

4.3.4.2 Information Quality

The findings in Table 4.9 and Figure 4.12 reveal that majority of the organizations' BI maturity were rated at level 3 "Defined" (44.2 percent) and level 4 "Managed" (40.4 percent). The former indicated that their information were integrated and aligned to organizational quality requirements, whereas the latter said that their information quality were enhanced through validity assessment, transformation control, and enhancement. There were 9.6 percent of organizations said that their information were locally useful but inconsistent, which is the indicative of level 2 “Repeatable”.

In contrast, there were 3.8 percent of organizations rated level 5 “Optimizing” where their information were and continually improved and treated as a product. Only a small number of organizations (1.9 percent) at level 1 “Initial” said that their information were not ready by the time of use and outdated due to information overload.

4.3.4.3 KPIs (Key Performance Indicators)

From Table 4.9 and Figure 4.12, it was found that 44.2 percent of organizations’ BI maturity were rated at level 3 (Defined) where their function-based KPIs were supplemented with some process-based KPIs. This was followed by 34.6 percent of organizations that rated level 4 (Managed) since their KPIs focused on achieving enterprise-wide integration. Next, there were 11.5 percent of organizations’ Bi maturity were rated at level 2 (Repeatable) where their KPIs were only function-based and non-integrated. Only a small number of organizations (5.8 percent) achieved level 5 (Optimizing) where their KPIs focused on external and cross-enterprise processes. The rest of the organizations (3.8 percent) said that their KPIs were financial-based and developed on an ad-hoc basis.

4.3.4.4 Summary of the findings on outcome dimension

Overall, the findings reported in Table 4.9 and Figure 4.12 show that majority of the participating organizations achieved level 3 (Defined) of the BI maturity for all of the components in outcome dimension. Table 4.10 lists the mean scores for each component in outcome dimension.

Table 4.10: Descriptive analysis for outcome dimension and the maturity level

Component	Mean	Std. Dev.
Data quality	3.13	0.69
Information quality	3.35	0.79
KPIs	3.27	0.89

From Table 4.10, it can be seen that the information quality component attained the highest average mean score (3.35). This implies that most of participating organizations recognize the value of providing high quality information to knowledge workers. This was an evident that organizations with higher maturity rating usually align information quality management processes to their organizational standards and policies.

Then, this was followed by the KPIs component with average mean score of 3.27. It appears that KPIs in most of the participating organizations are function-based and process-based. This means that the KPIs are mostly used to measure the efficiency and effectiveness of the business processes. On the other hand, the data quality component had the lowest average mean score (2.31). This might be due to some organizations are still using reactive data cleansing approach which focuses only on solving problems of existing data extracted from multiple data sources. Advancing to a higher level requires the need of constantly checking data quality against business rules, flagging data errors, as well as calculating data quality metrics. Besides, another reason could be related to the lower degree of data governance which in turn affecting level of data quality.

4.3.5 Overall Findings on the Four Dimensions in the MOBI Maturity Model

Table 4.11 reveals an overview of average mean scores that 52 participating organizations attained for each dimension. Overall, technology and outcome dimensions had achieved the highest BI maturity with average mean score of 3.25 respectively. Whereas, the process dimension had attained the lowest BI maturity with average mean score of 3.00.

Table 4.11: Average mean scores of each dimension built into the MOBI maturity model

Dimension	**Mean**	**Std. Dev.**
Organizational management	3.13	0.75
Process	3.00	0.66
Technology	3.25	0.67
Outcome	3.25	0.67
Overall BI maturity	**3.16**	**0.57**

The findings revealed that all four dimensions maturing scores are close to 3.00. This implies that the participating organizations have put much emphasis on their BI tools and architectures, as well as BI quality in term of data, information, and KPIs. Furthermore, it seems that the organizations did not provide a strong platform for governance and training at various levels to support BI workflows and business processes. These findings highlights that it is not just one dimension that affects the level of BI maturity an organization achieved. Rather, several dimensions usually come together to contribute to BI maturity level.

In this research, it was found that none of the participating organizations have achieved level 5. Out of 52 organizations, Organization 13 (in insurance industry) attained the highest maturity score of 4.42 across all four dimensions. On the contrary, Organization 28 (in banking industry) attained the lowest maturity score of 2.04 across all four dimensions. This may be attributed to the low usage of BI technologies and poorly managed the BI outcome. The radar chart as shown in Figure 4.13 shows a more detailed view of BI maturity assessment for these two organizations, which illustrates the level of achievement for each component within the four dimensions. This assessment provides insights into the strengths and weaknesses of organizations in managing their BI initiatives. For instance, the change management component had achieved higher maturity level in Organization 13 (Level 4) compared to Organization 28 (Level 1).

In addition, the radar chart (Figure 4.13) showed that organization 13 rated between maturity level 3 and level 5 for all the dimensions. This may imply that they have a relatively good organizational structure and sophisticated technology infrastructure to manage their BI related processes and outcome-based quality of BI initiatives.

Further, the descriptive statistics seem to be the most appropriate method to assess the current maturity level of BI implementation in Malaysian organizations, which has been discussed in chapter 3. Means, standard deviation (Std. Dev.), frequency and percentage of cases were generated to find out the number of participating organizations that rating the maturity level for each component built into the four dimensions of BI namely organizational management, process, technology, and outcome. The findings are revealed in Tables 4.3 and 4.4 (organizational management dimension), 4.5 and 4.6 (process dimension), 4.7 and 4.8 (technology dimension), and 4.9 and 4.10 (outcome dimension), that have been discussed in previous section.

The average response for each of the dimensions is around the midpoint (3) of the five-point scale (see Table 4.11). This means that the participating organizations show a moderate level of the maturity for the four dimensions to assess the BI maturity in their organizations. Then, the overall BI maturity score was calculated based on the average mean scores attained for the four dimensions. As can be seen in Table 4.11, the average mean score of the overall BI maturity is 3.16. This reflects that the Malaysian organizations are still at moderate level of BI maturity although they have achieved quite well across four dimensions, especially the technology and outcome dimensions.

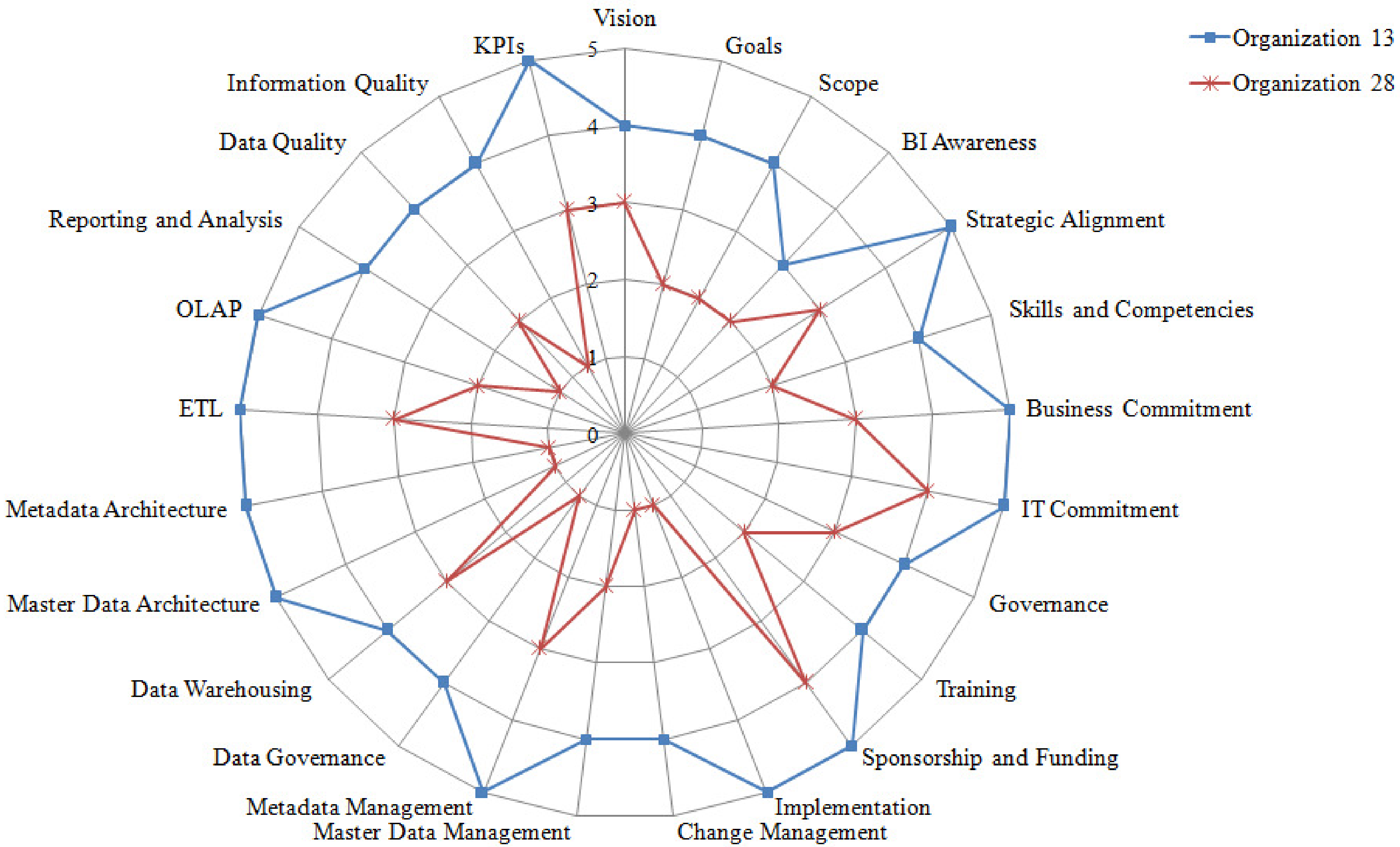


Figure 4.13: An example of the detailed view of BI maturity assessment for two selected organizations

Focusing solely on one or two dimensions does not increase overall BI maturity. BI implementation is an ongoing set of activities involving resources and decision making that could affect every part of business. Therefore, it is important to consider other aspects related to organizational and process, such as governance, strategic alignment, data management, and change management, as the determinant of BI maturity. Identifying and understanding BI maturity from these different dimensions may help organizations in charting their BI implementation better thereby obtaining all the potential benefits from their BI investments.

4.4 The Results of Hypotheses Testing

Three hypotheses were formed and used to verify the research objective 3. This section presents the results of each analyzed hypothesis.

4.4.1 The Results of H1 Testing

The following null hypothesis was tested:

$H_0$1: The types of industry have no significant effect on the BI maturity.

As described in chapter 3, the independent-samples t-test was used to test H1 to examine whether the service and non-service industries have significant effects on the BI maturity. David and Sutton (2011) noted that if the significance of the t-test is low, it indicates a significant difference in the two means. The *p* value was found to be significant (t = 2.051, p = 0.046) (see

Tables 4.12 and 4.13). The data provide enough evidence to reject the null hypothesis ($p < 0.05$). Therefore, there was strong evidence to support H1 that the types of industry had significant effects on the BI maturity.

Table 4.12: Descriptive statistics for BI maturity level and types of industry

BI maturity level

Types of Industry	**N**	**Mean**	**Std. Dev.**
Service	32	3.28	0.57
Non-service	20	2.96	0.53

Table 4.13: T-test results for BI maturity level and types of industry

BI maturity level	**Levene's Test for Equality of Variance**		**T-test for Equality of Means**		
	F	Sig.	t	df	Sig. (2-tailed)
Equal variances assumed	0.349	0.555	2.051	50	0.046*
Equal variances not assumed			2.085	42.603	0.043

* $p < 0.05$

Note:
According to David and Sutton (2011), the value of equal variance assumed is applicable if the significance of the Levene's test is high (greater than 0.05). Since the *p*-value for Levene's test is large ($p = 0.555$), which is greater than 0.05, so we can assume that the equal variances assumed is not violated.

In addition to the hypothesis testing, further analysis was conducted which revealed more findings. The findings are presented using tables, line chart and radar charts in the subsequent paragraphs. As can be perceived through Figure 4.14, service industries obtained higher mean score for most of the components than the non-service industries, except master data management and master data architecture components. These findings were further elaborated in the following sub-sections.

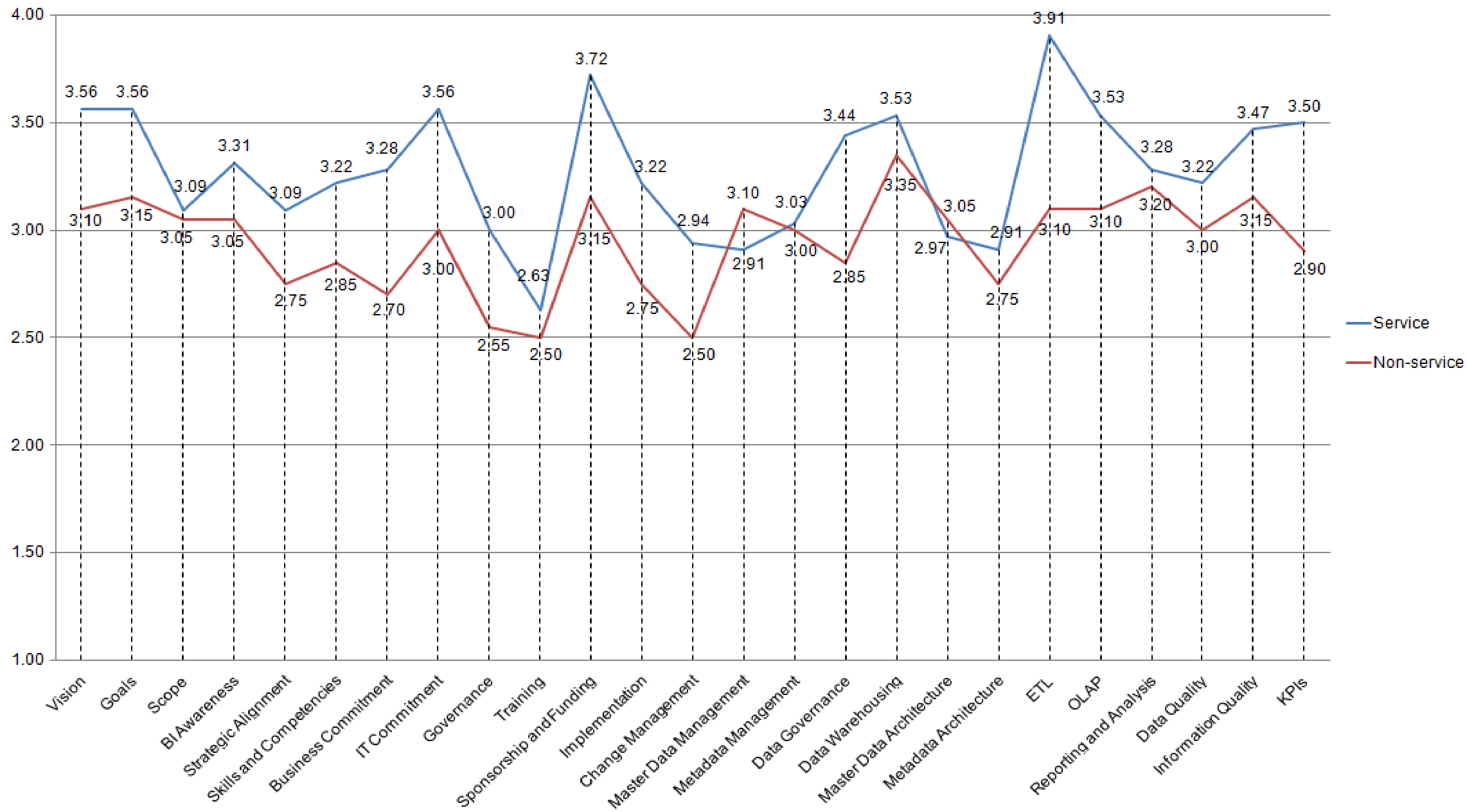


Figure 4.14: Comparative analysis of each component in all four dimensions by types of industry

For service industries, ETL component had the highest mean score of 3.91 while training component had the lowest mean score of 2.63. For non-service industries, data warehousing component had the highest mean score of 3.35 while both training and change management components had the lowest mean score of 2.50.

In addition, the results of the comparative analysis of each component that built into the four dimensions (i.e., organizational management, process, technology, and outcome) to measure the BI maturity based on types of industry (i.e. service and non-services industries) are further discussed as in the following subsections. Past studies (e.g. Olbrich et al., 2012; Raber et al., 2013) claimed that the environment of an organization could affect the evolution of BI maturity. The study of Shanks et al. (2012) also highlighted that service industries are very information-intensive, requiring more scrutinizing and reporting functionalities to address explorative and routine problems than non-service industries.

I. Organizational management dimension by types of industry

Table 4.14 and Figure 4.15 show the comparison between service and non-service organizations based on the 11 components of the organizational management dimension.

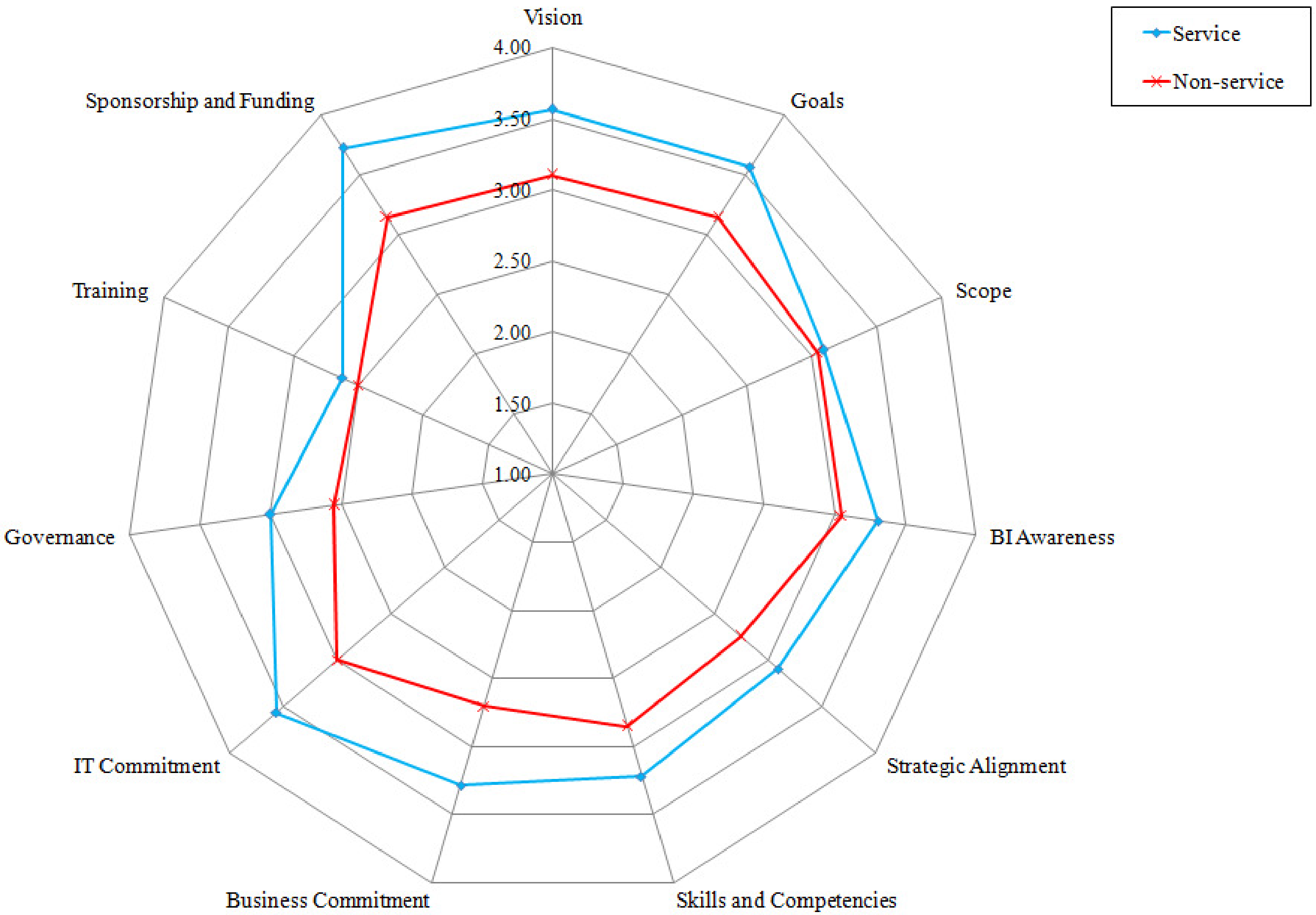


Figure 4.15: Comparative analysis of each component in the organizational management dimension by types of industry

Table 4.14: Descriptive analysis for organizational management dimension and types of industry

Component	Types of Industry			
	Service		Non-service	
	Mean	Std. Dev.	Mean	Std. Dev.
Vision	3.56	0.88	3.10	0.79
Goals	3.56	0.84	3.15	0.81
Scope	3.09	1.00	3.05	1.05
BI awareness	3.31	0.90	3.05	1.00
Strategic alignment	3.09	1.17	2.75	0.91
Skill and competencies	3.22	0.75	2.85	0.59
Business commitment	3.28	1.02	2.70	0.73
IT commitment	3.56	1.11	3.00	0.86
Governance	3.00	1.16	2.55	0.89
Training	2.63	0.79	2.50	0.69
Sponsorship and funding	3.72	1.40	3.15	1.63

As depicted in Table 4.14 and Figure 4.15, the results show that the organizational management from service industries achieved higher mean score for all components than the non-service industries. BI is often associated with service industries, especially finance and healthcare industries. Specifically, service organizations focus on the information flow and interaction between people (e.g. customers) to deliver quality service. Thus, service organizations are more likely to have a stronger organizational focus especially on sponsorship and funding component with mean score of 3.72, followed by vision, goals, and IT commitment components with mean score of 3.56 respectively.

Further, since service organizations are labour- and knowledge-intensive, the skills and competencies of service employees are higher than non-service organizations. In term of training component, both industries have a similar maturity level (i.e., level 2). This is clearly affected by the business and IT strategies developed by their organizations.

On the other hand, non-service organizations scored lower maturity level (i.e., level 2) for strategic alignment, governance, and business commitment components compared to service organizations. This could be probably due to non-service organizations focus largely on internal operations instead of service processes and view BI as an IT-driven initiative.

II. Process dimension by types of industry

Table 4.15 and Figure 4.16 show the comparison between service and non-service organizations based on the five components of the process dimension. The results reveal that organizations from service industries achieved higher mean score for almost all components than the organizations from non-service industries, except for master data management component.

Table 4.15: Descriptive analysis for process dimension and types of industry

Component	Types of Industry			
	Service		Non-service	
	Mean	Std. Dev.	Mean	Std. Dev.
Implementation	3.22	1.04	2.75	0.55
Change management	2.94	1.11	2.50	0.76
Master data management	2.91	1.06	3.10	0.91
Metadata management	3.03	1.23	3.00	1.21
Data governance	3.44	1.08	2.85	0.81

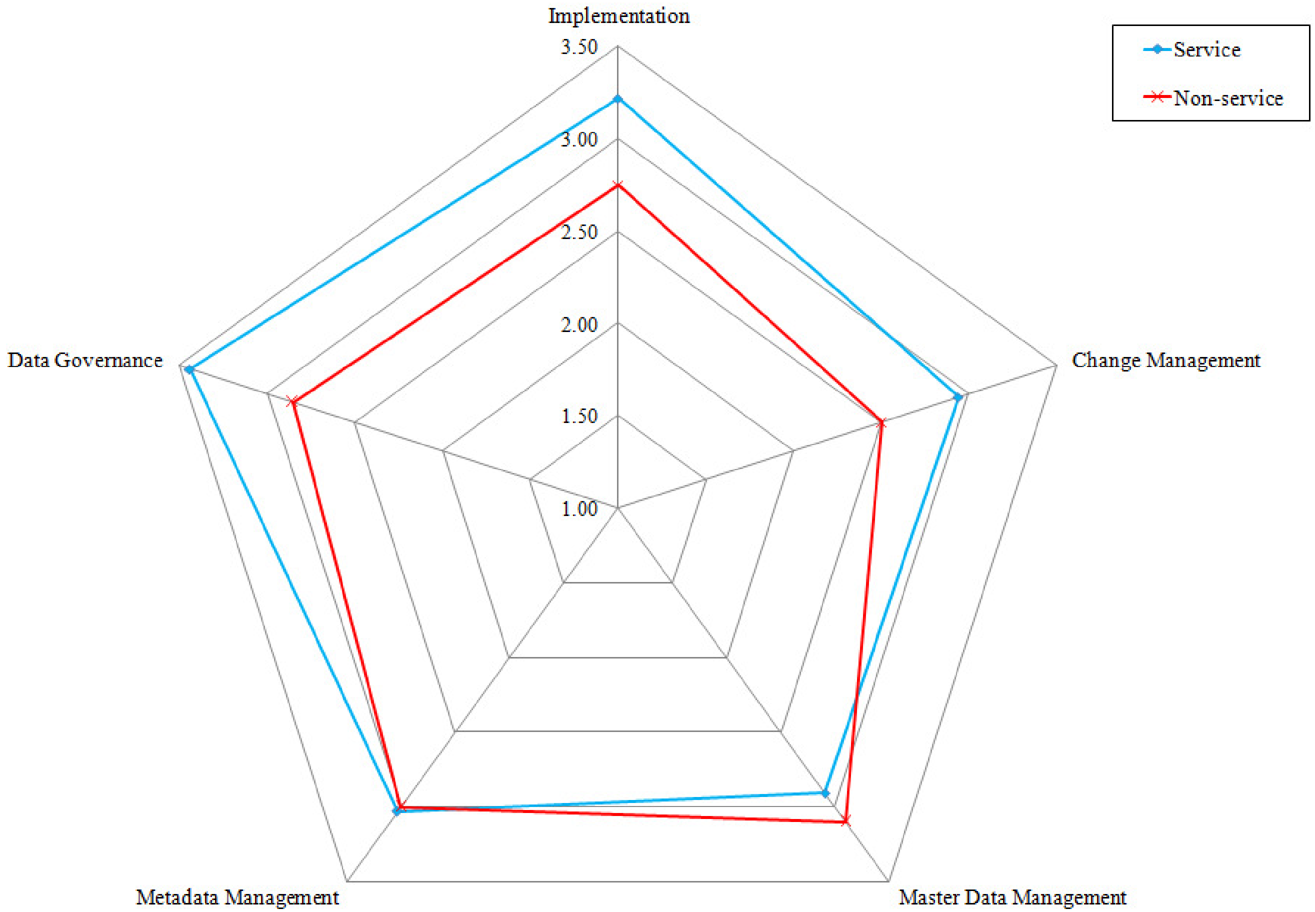


Figure 4.16: Comparative analysis of each component in the process dimension by types of industry

In particular, non-service organizations have recorded a lower maturity level (i.e., level 2) for implementation and data governance components. This may be related to the low degree of business commitment for coordination, product diversification, and highly complex supply chains making the non-service organizations (e.g. manufacturing and retail industries) difficult to evolve to a higher level.

In term of change management component, service organizations scored slightly higher although both industries have a lower maturity level (i.e., level 2). This implies that service organizations are putting more efforts in handling changes since the business processes in service environment are normally cross-organizational boundaries. Additionally, both industries have a similar maturity level (i.e., level 3) for metadata management component. This signifies that the organizations have not centrally documented policies and standards regarding the creation and maintenance of metadata, which contributes to the moderate level of metadata management.

For master data management component, service organizations fall within level 2 (mean = 2.91) although it is very close to non-service organizations which are situated at level 3 (mean = 3.10). This indicates that master data management is higher importance to non-service organizations. Possible reason could be due to the larger need in the maintenance and optimization of the substantial data volumes about products and raw materials in non-service organizations, especially for manufacturing and semiconductors industries. In contrast, service organizations deal with services and other intangible goods that cannot be depicted easily as concrete data, compared to physical goods.

III. Technology dimension by types of industry

Table 4.16 and Figure 4.17 show the comparison between service and non-service organizations based on the six components of the technology dimension.

Table 4.16: Descriptive analysis for technology dimension and types of industry

Component	Types of Industry			
	Service		Non-service	
	Mean	Std. Dev.	Mean	Std. Dev.
Data warehousing	3.53	0.80	3.35	0.75
Master data architecture	2.97	1.23	3.05	0.89
Metadata architecture	2.91	1.15	2.75	0.72
ETL	3.91	0.73	3.10	0.85
OLAP	3.53	0.92	3.10	0.97
Reporting and analysis	3.28	1.02	3.20	0.83

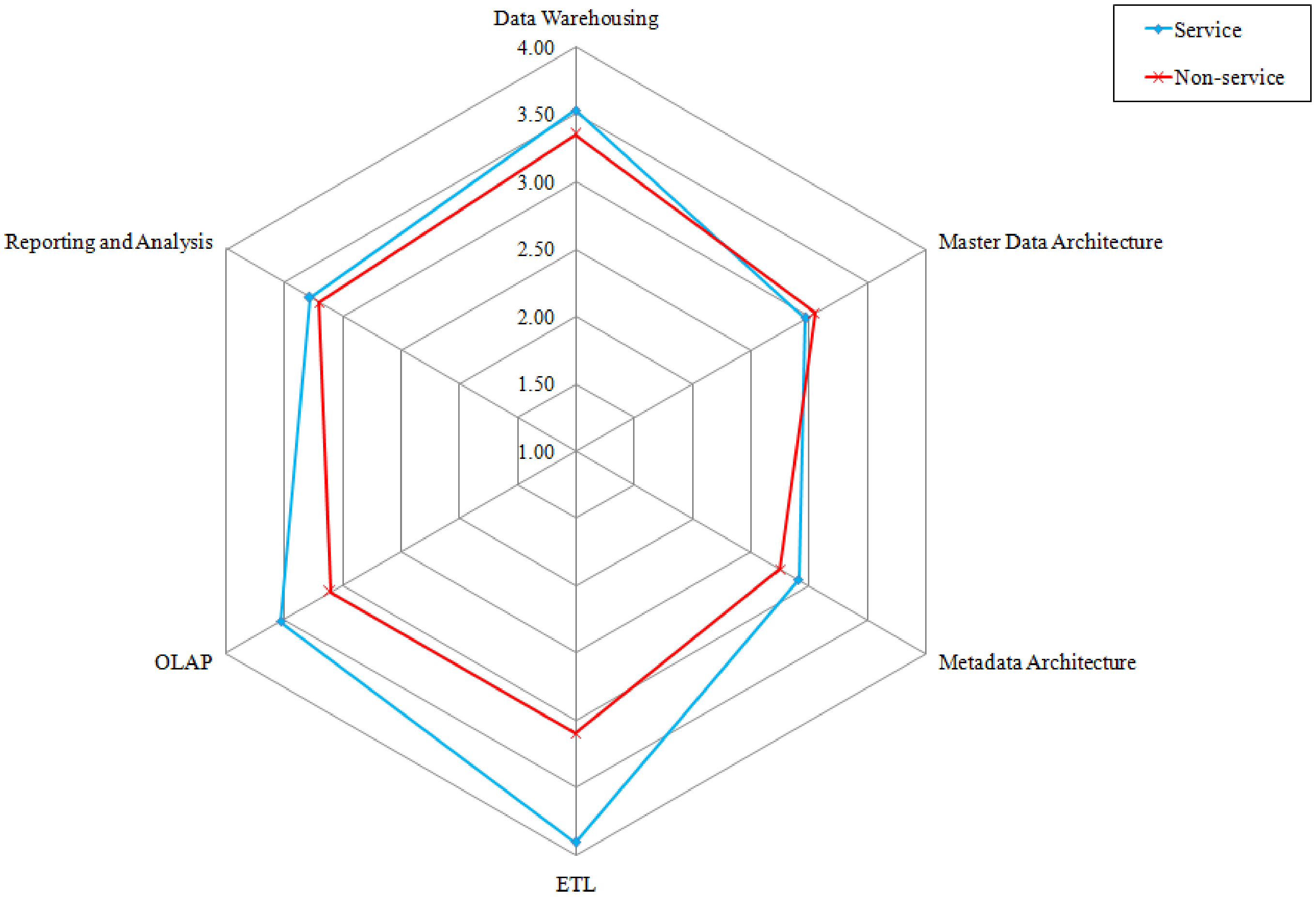


Figure 4.17: Comparative analysis of each component in the technology dimension by types of industry

From Table 4.16, the results show that organizations from service industries achieved higher mean score for all the components than the organizations from non-service industries, except master data architecture component. Specifically, service organizations scored at level 3 with mean score of 3.05 while non-service scored at level 2 with mean score of 2.97. This difference could be explained by the unique requirements and complexity of decision making on non-service environment which places an emphasis on the master data quality in facilitating the exchange of information between applications.

Of the four components (i.e., data warehousing, ETL, OLAP, and reporting and analysis), both industries attained a similar maturity level (i.e., level 3). In terms of ETL and OLAP components, the mean scores of service industries are fairly higher than non-service industries. This result could be due to service organizations place greater demand for more advanced functionalities to support customer-related activities in real time basis.

Besides, there is only a slight difference in mean score between service (mean = 3.53) and non-services (mean = 3.35) industries for data warehousing component. This could be due to some service organizations are moving towards real time data warehousing with the implementation of BI services in business transaction workflow. As a result, this puts service industries higher on data warehousing component than non-services industries. With regard to reporting and analysis component, the mean scores for both service and non-service industries are about the same (3.28 and 3.20 respectively). Apart from that, both industries were positioned in the same maturity level (i.e., level 2) for metadata architecture component with mean score of 2.91 and 2.75 respectively.

IV. Outcome dimension by types of industry

Table 4.17 and Figure 4.18 show the comparison between service and non-service organizations based on the three components of the outcome dimension.

Table 4.17: Descriptive analysis for outcome dimension and types of industry

Component	Types of Industry			
	Service		Non-service	
	Mean	Std. Dev.	Mean	Std. Dev.
Data quality	3.22	0.71	3.00	0.65
Information quality	3.47	0.80	3.15	0.75
KPIs	3.50	0.72	2.90	1.02

The results show that organizations from service industries achieved higher mean scores for all components compared to the organizations from non-service industries. With regard to data quality and information quality components, both industries fall within same maturity level (i.e., level 3). Unlike data within non-service environment that can only be used for single products, data and information within service environment can be produced and consumed by end users simultaneously. This explains why service industries place more efforts on improving quality of data and information.

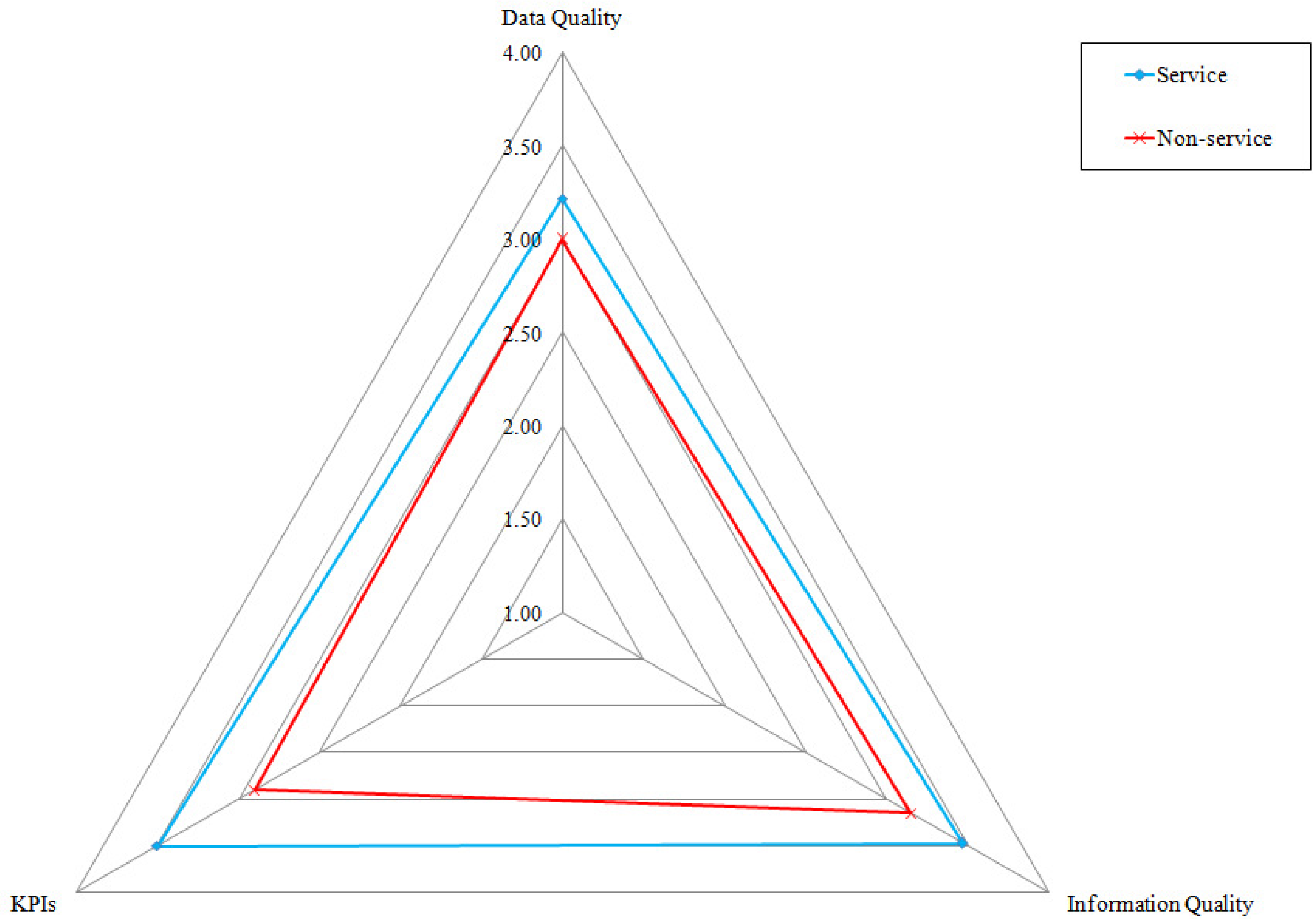


Figure 4.18: Comparative analysis of each component in the outcome dimension by types of industry

In term of KPIs component, service organizations scored higher maturity level (i.e., level 3) with mean score of 3.50 than non-service organization with mean score of 2.90. This could be attributed to the higher degree of integration and improvement in cross-functional service processes that are customer-oriented. For instance, service organizations in banking industries focus more on KPIs such as service time and waiting time. Unlike non-service industries, it appears that their KPIs are still function-oriented such as product quality and inventory balances.

4.4.2 The Results of H2 Testing

The following null hypothesis was tested:

$H_0 2$: The organizational size has no significant effect on the BI maturity.

As described in chapter 3, the One-Way ANOVA test was used to test $H_0 2$ to analyze whether or not the organizational size has a significant effect on BI maturity. The p value was large (p = 0.740) indicating that the null hypothesis could not be rejected ($p > 0.05$) (see Tables 4.18 and 4.19). Hence, there was not enough evidence to support H2. This indicates that the organizational size had no significant effect on BI maturity.

Table 4.18: Descriptive statistics for BI maturity level and organizational size

BI maturity level

Organizational Size	**N**	**Mean**	**Std. Dev.**
Small (1 – 1000)	16	3.16	0.48
Medium (1001 – 5000)	19	3.23	0.57
Large (> 5000)	17	3.08	0.66

Table 4.19: ANOVA results for BI maturity level and organizational size

ANOVA Table		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
BIMat * OrgSize	Between Groups	0.201	2	0.100	0.303	0.740
	Within Groups	16.242	49	0.331		

In general, the larger the organization, the more mature the organization is. However, the results show that the mean score of three size groups are relatively close to each other (see Table 4.19). The research findings differ from previous studies (e.g. Elbashir et al., 2008; Ramamurthy et al., 2008; Raber et al., 2013) which indicated that organizational size has an impact on BI initiative. This reflects that even though small- and medium-sized organizations do not involve in big scale of operations as large-sized organization, they have been able to leverage the same advantages from the best practice processes and technology improvements that were developed specifically for larger organizations. Small- and medium-sized organizations are gearing up to capitalize on the benefits of BI and moving towards a higher BI maturity level similar to larger organizations. Managing Director of SAS Malaysia, Andrew Tan stated that BI solutions on the market today are designed to fit all needs and can be deployed easily by organizations of all sizes (SAS, 2014). Thus, smaller organizations are able to concentrate on strategic alignment and grow their businesses.

Although the result was obtained with a limited sample size, it was supported by the study of Levy and Powell (2004) which stated that "small- and medium-sized enterprises (SMEs) have as much need for BI as large firms" (p. 24). The study of Canes (2009) and Guarda et al. (2013) also reported that most of today's SMEs experience similar BI challenges as large organizations. Hence, the size of an organization may not matter especially in the advancement of technology aspect.

Furthermore, the comparative analysis of each component that built into the four dimensions (i.e., organizational management, process, technology, and outcome) to measure the BI maturity based on organizational size (i.e. small-, medium- and large-sized organizations) was conducted which revealed more findings. The findings are presented using tables and radar charts in the subsequent paragraphs.

I. Organizational management dimension by organizational size

Table 4.20 and Figure 4.19 depict the comparison of each component in the organizational management dimension based on organizational size.

With regard to business commitment component, medium-sized organization scored slightly lower maturity score (mean = 2.95) compared to small- (mean = 3.12) and large-sized (mean = 3.13) organizations (see Table

4.20 and Figure 4.19). This implies that medium-sized organizations are shifting towards business-driven BI initiatives. In term of governance component, small-sized organizations scored slightly higher maturity score (mean = 3.00) than medium- (mean = 2.95) and large-sized (mean = 2.53) organizations. This implies that they still lack of necessary authority on BI-related decisions.

Apart from that, medium-sized organizations scored higher maturity score (mean = 4.05) than small- (mean = 3.06) and medium-sized (mean = 3.29) organizations for the sponsorship and funding component. This was probably due to medium-sized organizations recognizing the importance of obtaining high level of sponsorship and funding to increase end user adoption and greater access to resources. Meantime, it was evident that medium-sized organizations scored higher mean score for the scope component (mean = 3.11) than small- and large-sized organizations with the mean score of 3.06 respectively.

Table 4.20: Descriptive analysis for organizational management dimension and organizational size

Component	Organizational Size					
	Small		Medium		Large	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Vision	3.31	1.01	3.37	0.90	3.47	0.72
Goals	3.31	1.20	3.47	0.61	3.41	0.71
Scope	3.06	1.12	3.11	0.99	3.06	0.97
BI awareness	3.31	1.08	3.16	0.90	3.18	0.88
Strategic alignment	2.94	1.24	2.84	1.17	3.12	0.86
Skill and competencies	3.13	0.62	3.11	0.66	3.00	0.87
Business commitment	3.13	1.09	2.95	0.97	3.12	0.86
IT commitment	3.69	1.20	3.37	0.96	3.00	0.94
Governance	3.00	1.10	2.95	0.97	2.53	1.18
Training	2.56	0.63	2.68	0.89	2.47	0.72
Sponsorship and funding	3.06	1.61	4.05	1.27	3.29	1.53

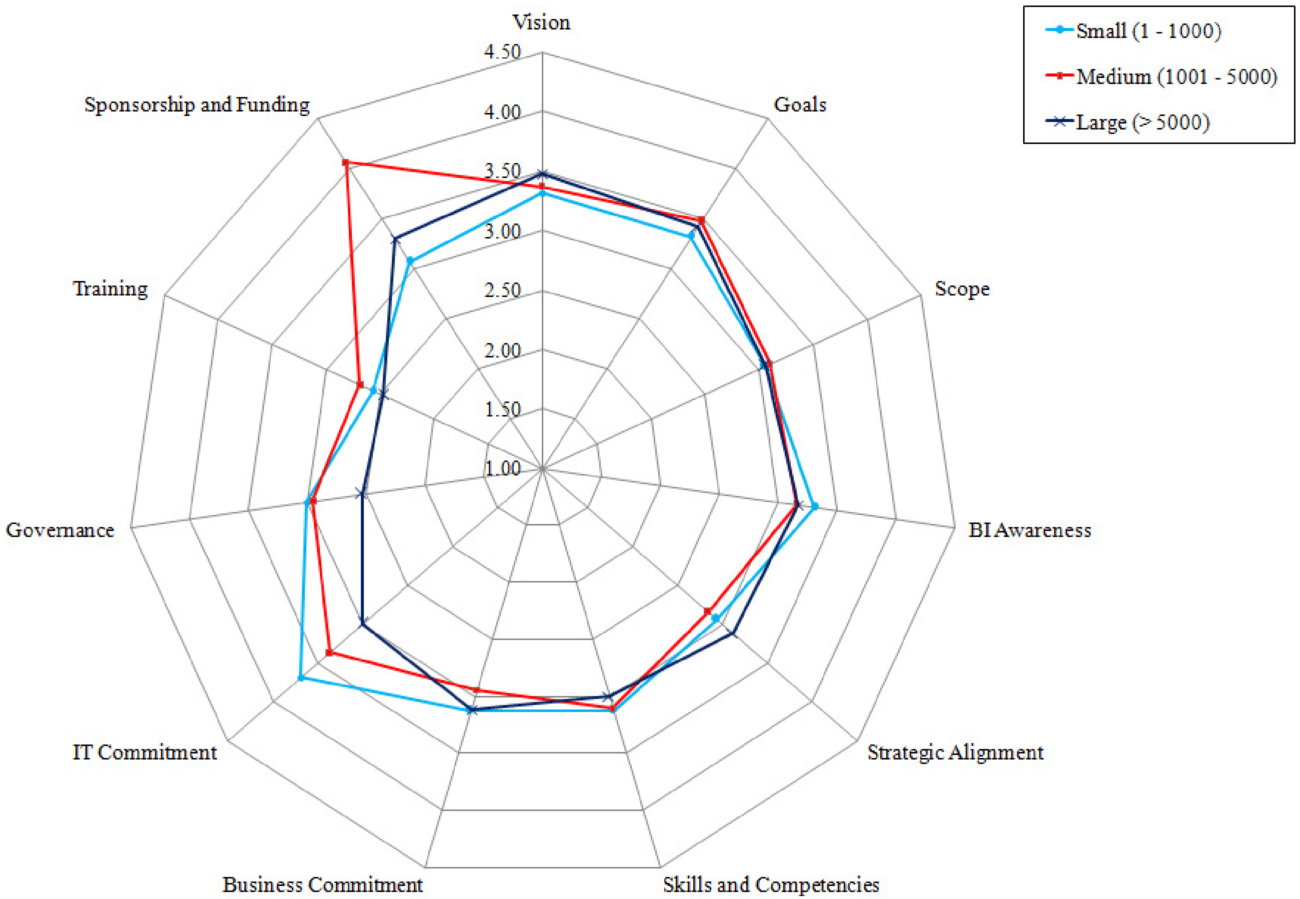


Figure 4.19: Comparative analysis of each component in the organizational management dimension by organizational size

II. Process dimension by organizational size

Table 4.21 and Figure 4.20 illustrate the comparison of each component in process dimension based on organizational size. The results showed that three groups of organizations have a similar maturity level for change management (i.e., level 2) and data governance (i.e., level 3) components.

Table 4.21: Descriptive analysis for process dimension and organizational size

Component	Organizational Size					
	Small		Medium		Large	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Implementation	2.94	0.85	3.05	0.78	3.12	1.11
Change management	2.75	1.13	2.79	0.79	2.76	1.15
Master data management	3.13	0.96	2.95	1.13	2.88	0.93
Metadata management	3.06	1.00	3.11	1.33	2.88	1.32
Data governance	3.13	0.96	3.47	0.84	3.00	1.23

With regard to implementation component, the results reveal that large-sized organizations scored higher mean score (mean = 3.12), followed by medium- (mean = 3.05) and small-sized (mean = 2.94) organizations. One of the possible reasons for this result is the implementation strategy chosen by the organizations. Specifically, large- and medium-sized organizations tend to use phased approach. Although many small-sized organizations favoured phased approach but there is a few of organizations applied big-bang approach.

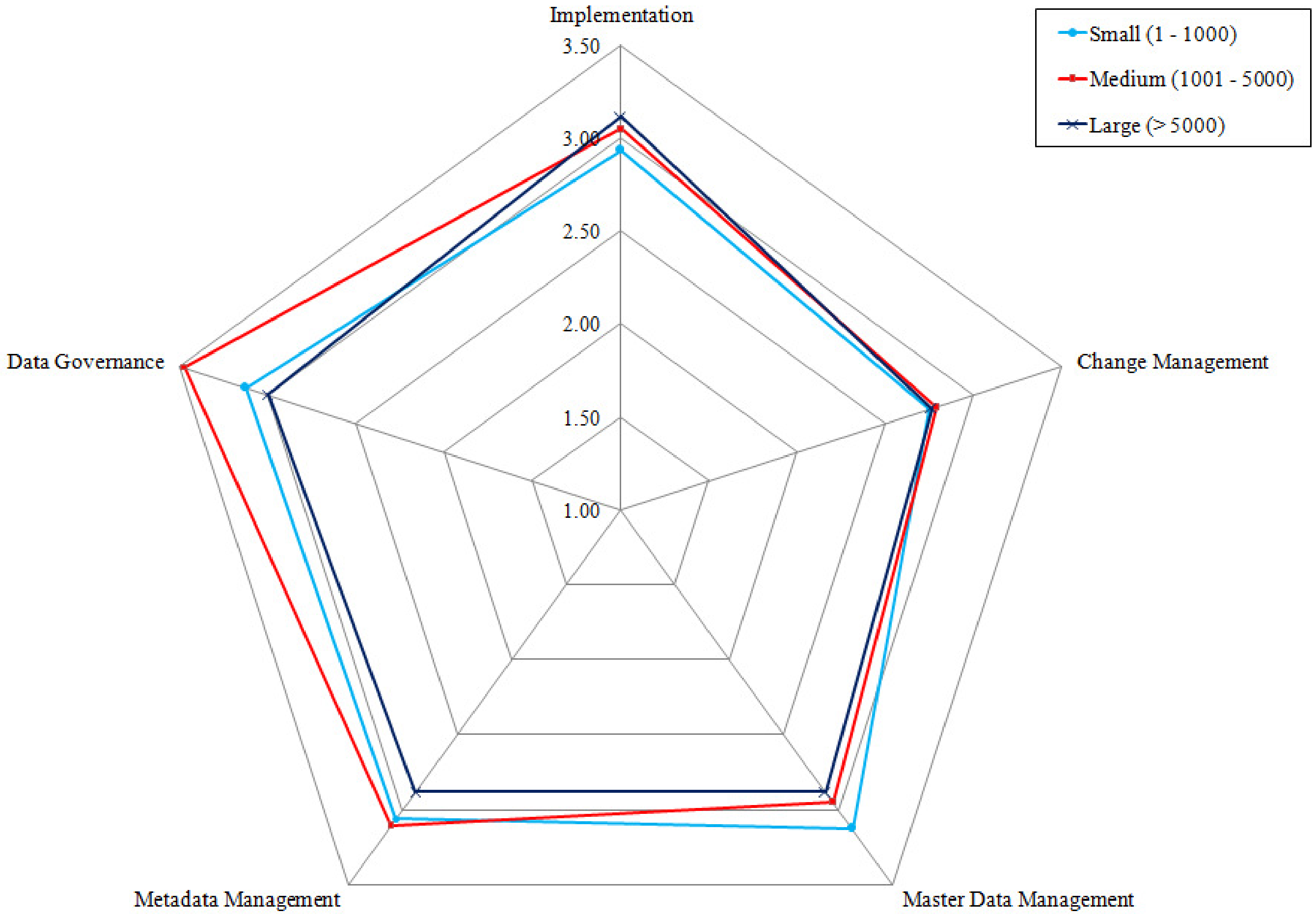


Figure 4.20: Comparative analysis of each component in the process dimension by organizational size

In term of master data management and metadata management components, small- and medium-sized organizations have slightly higher mean scores than large-sized organizations. Typically, bigger organizations have a larger amount of master data and metadata owned by different departments as well as more complex business processes to be handled. Consequently, it creates challenges to organizations to fully integrate their master data and metadata management enterprise-wide (Radcliffe 2007).

III. Technology dimension by organizational size

Table 4.22 and Figure 4.21 reveal the comparison of each component in the technology dimension based on organizational size. Out of six components in technology dimension, the results show that three groups of organizations have a similar maturity level for five components. Except for master data architecture component, medium-sized organizations have a higher maturity level (i.e., level 3) than small- and large-sized organizations (i.e., level 2). This could be related to the low degree of cross-functional collaboration and absence of enterprise-level architectural planning (Dyche and Levy, 2009).

With regard to data warehousing component, small-sized organizations have a mean score of 3.25 that is close to medium- and large-sized organizations with mean scores above 3.50. This implies that even small-sized organizations are now using data warehouses to meet rapidly growing business demands and maintain a competitive advantage over their competitors.

Although there is a gradient in maturity of metadata architecture component among the three groups of organizations (i.e., small-sized with mean score of 2.75, medium-sized with mean score of 2.84, and large-sized with mean score of 2.94), the mean score of these groups are relatively close to each other. Based on the survey findings, it was found that these organizations primarily focused on technical and operational metadata without prioritizing business metadata.

Table 4.22: Descriptive analysis for technology dimension and organizational size

Component	Organizational Size					
	Small		Medium		Large	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Data warehousing	3.25	0.86	3.58	0.77	3.53	0.72
Master data architecture	2.88	0.72	3.21	1.36	2.88	1.11
Metadata architecture	2.75	0.93	2.84	1.02	2.94	1.09
ETL	3.63	0.81	3.63	1.01	3.53	0.80
OLAP	3.00	1.10	3.63	0.90	3.41	0.80
Reporting and analysis	3.25	0.68	3.32	1.00	3.18	1.13

In term of ETL component, large-sized organizations have a slightly lower mean score of 3.53 compared to small- and medium-sized organizations with similar mean score of 3.63. Overall, this result reflects the widespread adoption of standard ETL tools for managing data validation and migration. Apart from that, small-sized organizations have a lower mean score of 3.00 for the OLAP component than medium- and large-sized organizations with mean scores above 3.40. This difference indicates that larger organizations show a greater interest implementation of integrated OLAP to automate cube maintenance tasks.

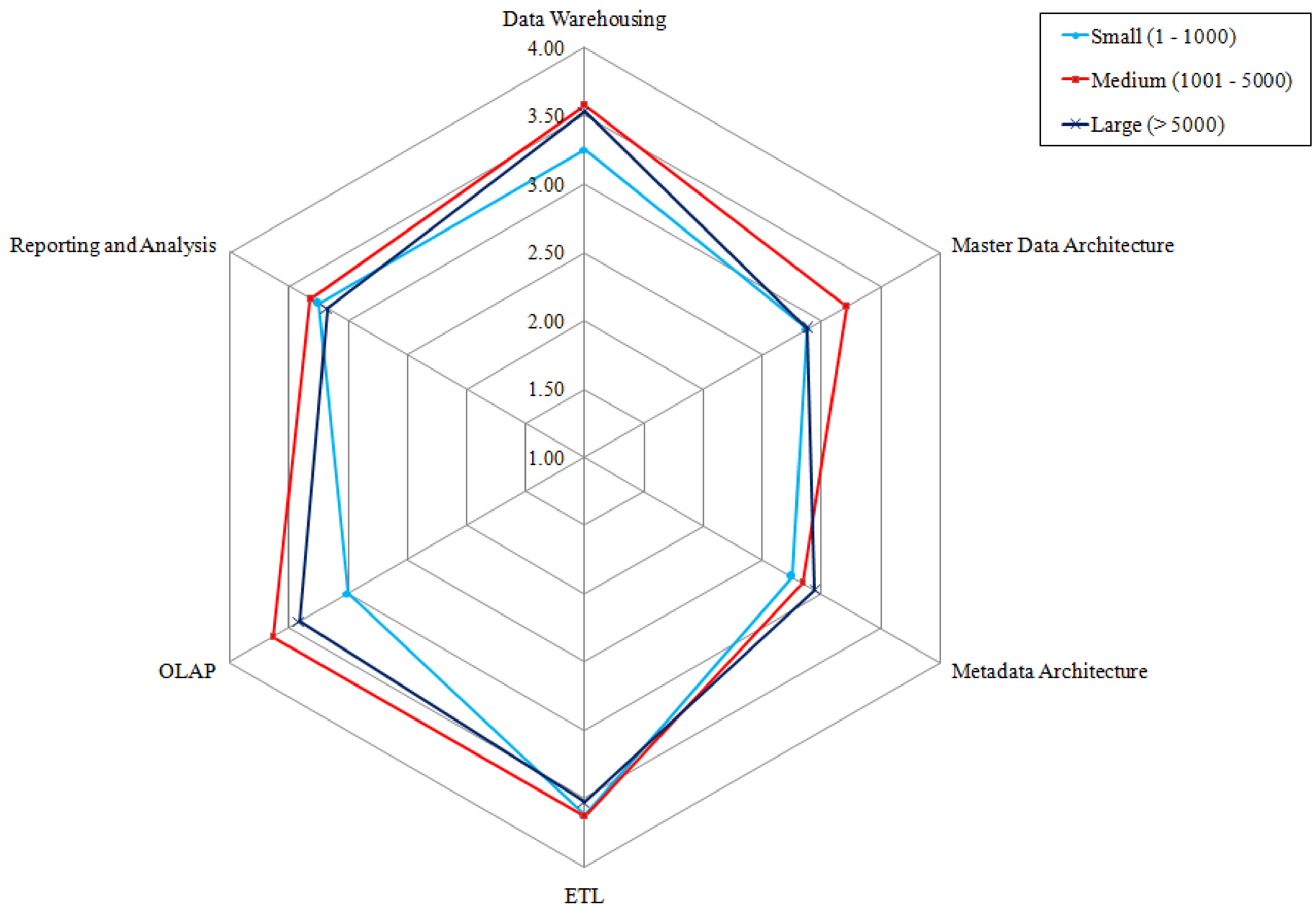


Figure 4.21: Comparative analysis of each component in the technology dimension by organizational size

As for the reporting and analysis component, small- and medium-sized organizations achieved a slightly higher mean score of 3.25 and 3.32 respectively, compared to large-sized organizations with mean score of 3.18. This highlights many small- and medium-sized organizations are now evolving towards advanced reporting and analysis capabilities.

IV. Outcome dimension by organizational size

Table 4.23 and Figure 4.22 illustrate the comparison of each component in the outcome dimension based on organizational size. The results show that three groups of organizations have a similar maturity level (i.e., level 3) for all the components.

With regard to data quality and information quality components, large-sized organizations scored lower mean scores compared to small- and medium-sized organizations. This could be attributed to the lack of standardization and integration strategies to handle large amounts of data and information across applications and databases (Davenport and Harris, 2007).

Table 4.23: Descriptive analysis for outcome dimension and organizational size

Component	Organizational Size					
	Small		Medium		Large	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Data quality	3.19	0.66	3.21	0.71	3.00	0.71
Information quality	3.56	0.73	3.42	0.77	3.06	0.83
KPIs	3.44	0.63	3.21	1.13	3.18	0.81

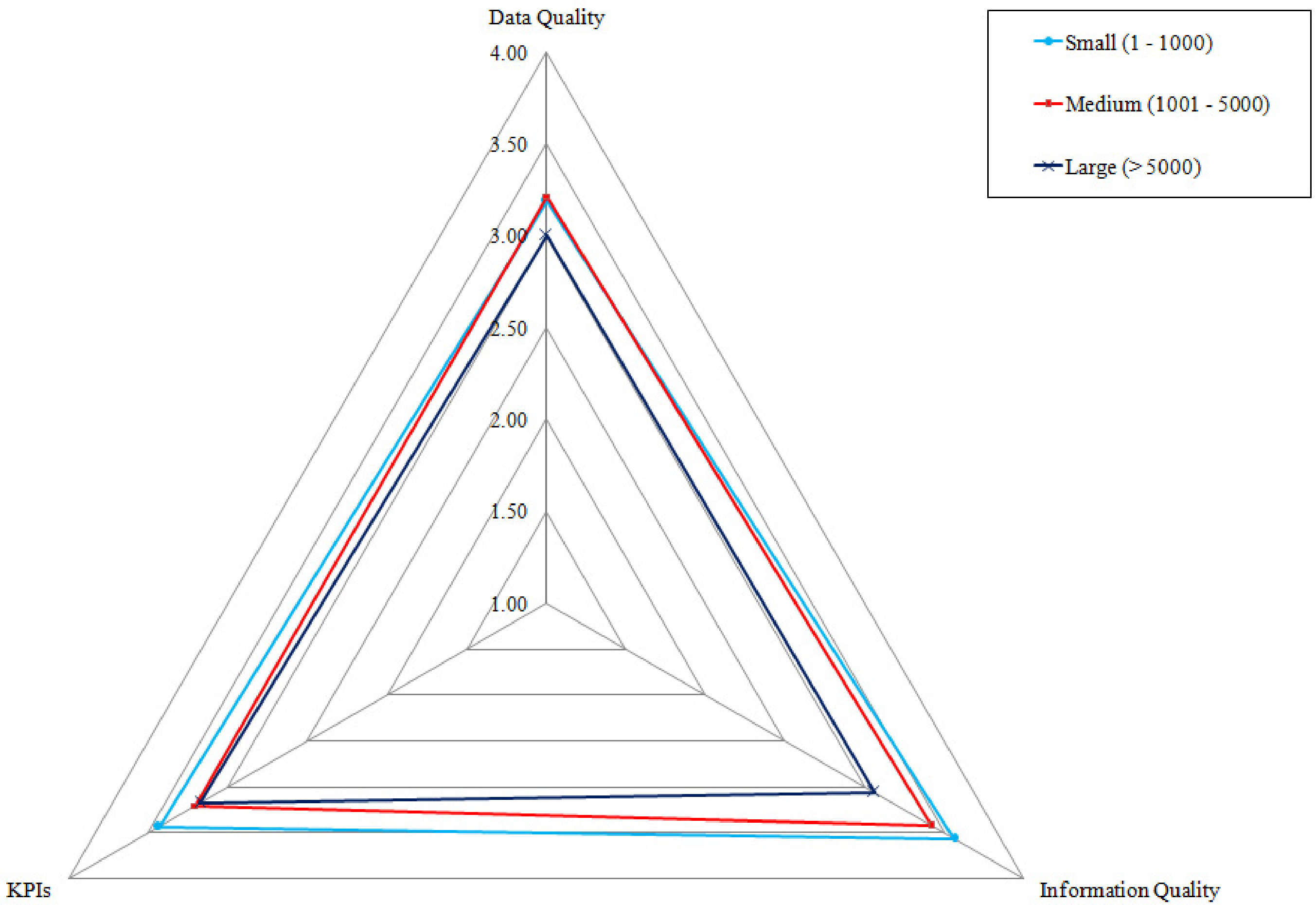


Figure 4.22: Comparative analysis of each component in the outcome dimension by organizational size

Furthermore, there is a gradient in maturity of KPIs component among the three groups of organizations (i.e., large-sized with mean score of 3.18, followed by medium-sized with mean score of 3.21, and small-sized with mean score of 3.44). Possible reason could be that smaller organizations with narrow business focus have lesser KPIs, whereas larger organizations have multiple departments making it difficult to share and integrate diversified KPIs which in turn leading to lower maturity.

4.4.3 The Results of H3 Testing

The following null hypothesis was tested:

$H_0 3$: The age of BI initiatives has no significant effect on the BI maturity.

The One-Way ANOVA test was also used to test $H_0 3$ to examine whether or not the different ages of BI initiative have significant effects on BI maturity (which has been described in chapter 3). From the following statistics and ANOVA results (see Tables 4.24 and 4.25), the *p* value was rather large ($p = 0.155$) indicating that the null hypothesis could not be rejected ($p > 0.05$). Thus, there was not enough evidence to support H3. This indicates that the age of BI initiatives has no significant effect on the BI maturity.

Table 4.24: Descriptive statistics for BI maturity level and age of BI initiatives

BI maturity level

Age of BI Initiatives	**N**	**Mean**	**Std. Dev.**
Less than 5 years	14	2.91	0.69
5 – 6 years	18	3.24	0.47
More than 6 years	20	3.26	0.52

Table 4.25: ANOVA results for BI maturity level and age of BI initiatives

ANOVA Table		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
BIMat * AgeBI	Between Groups	1.206	2	0.603	1.940	0.155
	Within Groups	15.236	49	0.311		

Eckerson's study (2007a) reported that the BI initiatives that have existed for longer period of time indicate a high level of maturity. However, the results show that the mean score of three age groups are relatively close to each other (see Table 4.24). It can be seen that organizations that are new to BI could excel at their BI evolution due to the deployment of new technologies and adaptability to changes. Although the result was obtained with a limited sample size, it was supported by the study of Williams and Williams (2007) in which age difference is not a factor in determining BI maturity, rather it depends on the ability of an organization to align, leverage, and deliver BI. Hence, the age of BI initiatives may not matter in this research.

In addition, the comparative analysis of each component that built into the four dimensions (i.e., organizational management, process, technology, and outcome) to measure the BI maturity based on the age of BI initiatives was conducted which revealed more findings. The age of BI initiatives consists of three groups. The findings are presented using tables and radar charts in the subsequent paragraphs.

I. Organizational management dimension by age of BI initiatives

Table 4.26 and Figure 4.23 show the comparison of each component in the organizational management dimension based on age of BI initiatives. The results show that all the three age groups have similar maturity level (i.e., level 3) for vision, goals, business commitment, IT commitment, and sponsorship and funding components.

Table 4.26: Descriptive analysis for organizational management dimension and age of BI initiatives

Component	Age of BI initiatives					
	Less than 5 years		5 – 6 years		More than 6 years	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Vision	3.07	1.07	3.56	0.78	3.45	0.76
Goals	3.07	0.92	3.39	0.85	3.65	0.75
Scope	2.71	1.20	3.22	0.81	3.20	1.01
BI awareness	2.86	0.95	3.33	1.03	3.35	0.81
Strategic alignment	2.71	1.27	2.89	1.08	3.20	0.95
Skill and competencies	2.86	0.86	3.33	0.59	3.00	0.65
Business commitment	3.00	1.11	3.11	1.08	3.05	0.76
IT commitment	3.21	1.25	3.56	0.92	3.25	1.02
Governance	2.64	0.93	2.94	0.87	2.85	1.35
Training	2.36	0.84	2.83	0.79	2.50	0.61
Sponsorship and funding	3.43	1.70	3.44	1.50	3.60	1.43

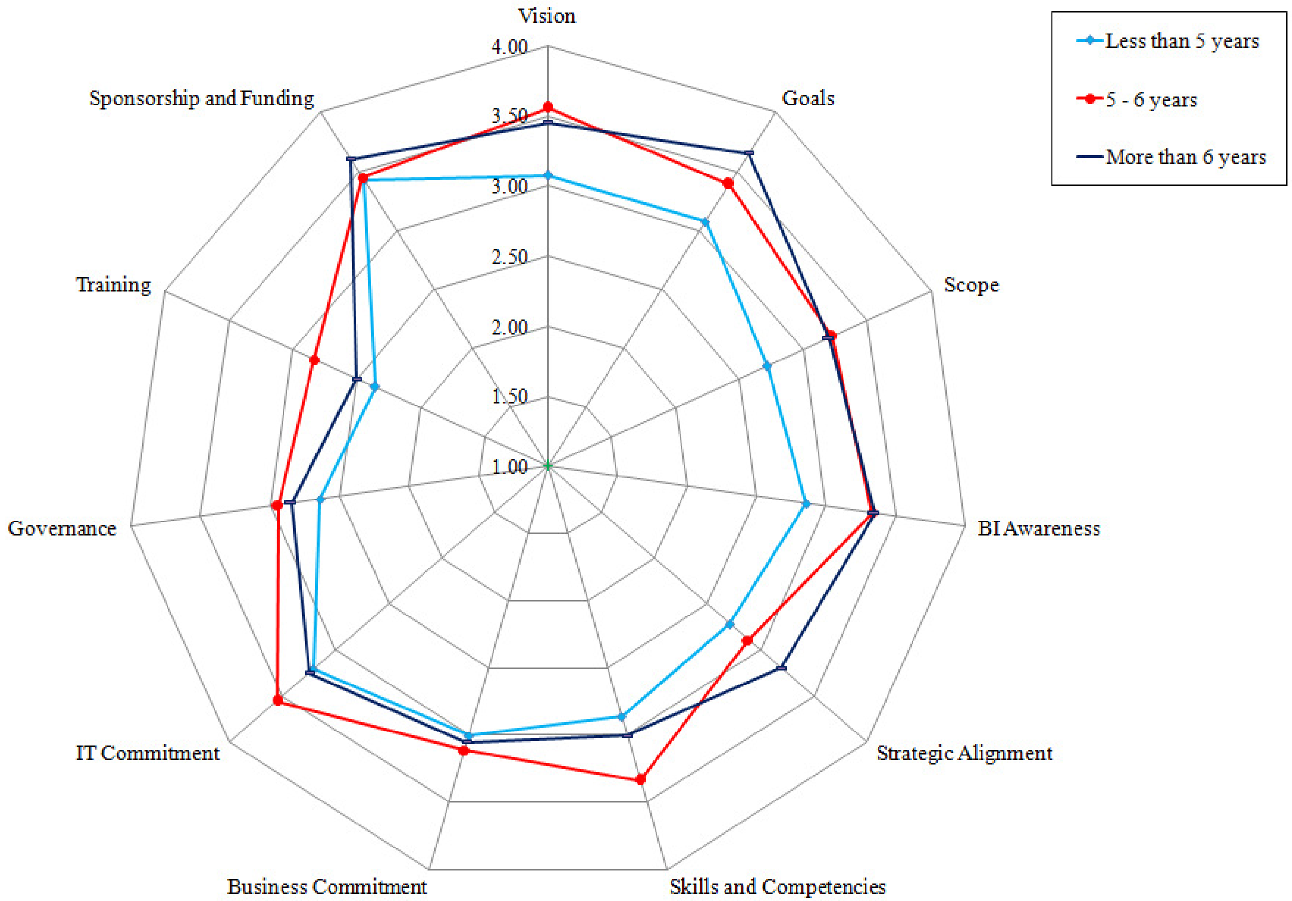


Figure 4.23: Comparative analysis of each component in the organizational management dimension by age of BI initiatives

Of the three age groups, BI initiatives that have existed for less than 5 years received lower maturity level (i.e., level 2) in term of scope, BI awareness, and skill and competencies components. This is particularly true since some of the organizations are still in the early stages of BI implementation.

With regard to strategic alignment component, BI initiatives that have existed for less than 5 years and 5 to 6 years received lower maturity level (i.e., level 2) than the remaining age groups (i.e., level 3). On top of that, all three age groups have similar maturity level (i.e., level 2) for governance and training components.

II. Process dimension by age of BI initiatives

Table 4.27 and Figure 4.24 show the comparison of each component in the process dimension based on age of BI initiatives.

Table 4.27: Descriptive analysis for process dimension and age of BI initiatives

Component	Age of BI initiatives					
	Less than 5 years		5 – 6 years		More than 6 years	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Implementation	3.21	1.19	2.94	0.64	3.00	0.92
Change management	2.43	1.02	2.94	1.00	2.85	0.99
Master data management	2.71	0.91	3.00	0.91	3.15	1.14
Metadata management	2.79	1.25	3.44	0.92	2.80	1.36
Data governance	3.29	1.14	3.11	0.96	3.25	1.02

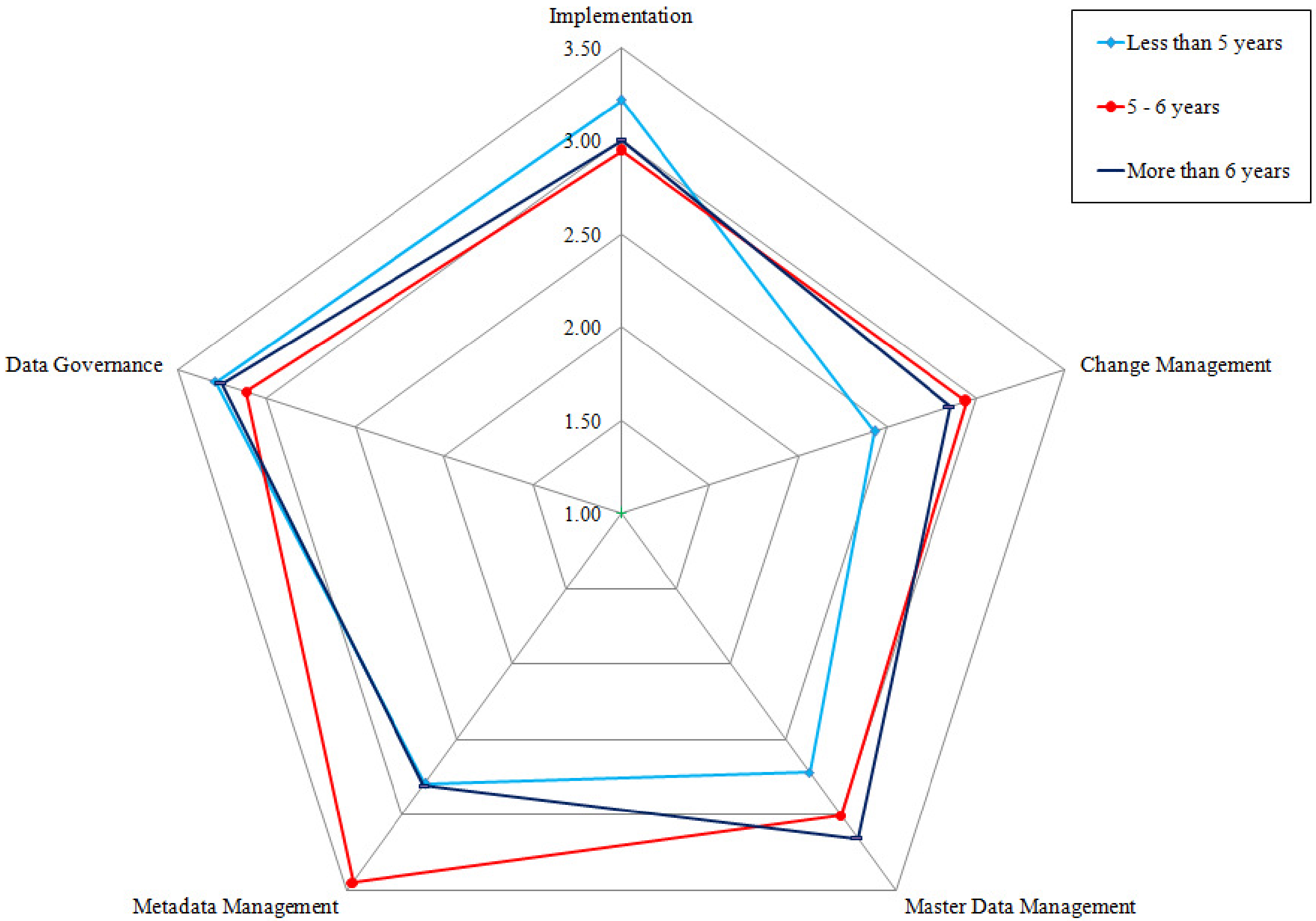


Figure 4.24: Comparative analysis of each component in the process dimension by age of BI initiatives

With regard to implementation component, BI initiatives that have existed for less than 5 years received highest mean score (mean = 3.21) than other two age groups. This implies that some organizations have accelerated their starting point of BI implementation resulting in higher maturity score. In term of change management component, all three age groups have similar maturity level (i.e., level 2) for change management component.

As organizations grow, there is a need for a fully centralized master data management system to manage large and complex master data. This was evident that BI initiatives that have existed for 5 to 6 years and more than 6 years scored higher maturity level (i.e., level 3) for master data management component than those have existed for less than 5 years.

In term of metadata management component, BI initiatives that have existed for 5 to 6 years recorded a higher maturity level (i.e., level 3) than the rest of the age groups (i.e., level 2). Based on the survey responses, it implies that there is limited awareness about the importance of maintenance, publication or sharing of metadata within some organizations resulting in a lower maturity level. Lastly, all the three age groups have similar maturity level (i.e., level 3) for data governance component.

III. Technology dimension by age of BI initiatives

Table 4.28 and Figure 4.25 show the comparison of each component in the technology dimension based on age of BI initiatives.

Table 4.28: Descriptive analysis for technology dimension and age of BI initiatives

Component	Age of BI initiatives					
	Less than 5 years		5 – 6 years		More than 6 years	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Data warehousing	3.07	0.83	3.39	0.78	3.80	0.62
Master data architecture	2.79	1.25	3.06	1.06	3.10	1.07
Metadata architecture	2.57	1.16	3.11	0.83	2.80	1.01
ETL	3.43	1.09	3.67	0.84	3.65	0.75
OLAP	3.00	1.24	3.33	0.84	3.65	0.75
Reporting and analysis	2.79	0.98	3.33	0.77	3.50	1.00

Overall, BI initiatives that have existed for less than 5 years received lowest mean scores for all the components, followed by BI initiatives that have existed for 5 to 6 years and more than 6 years. The results show that all three age groups have similar maturity level (i.e., level 3) for data warehousing, ETL, and OLAP components. With regard to master data architecture component, BI initiatives that have existed for less than 5 years achieved lower maturity level (i.e., level 2) than the remaining two age groups.

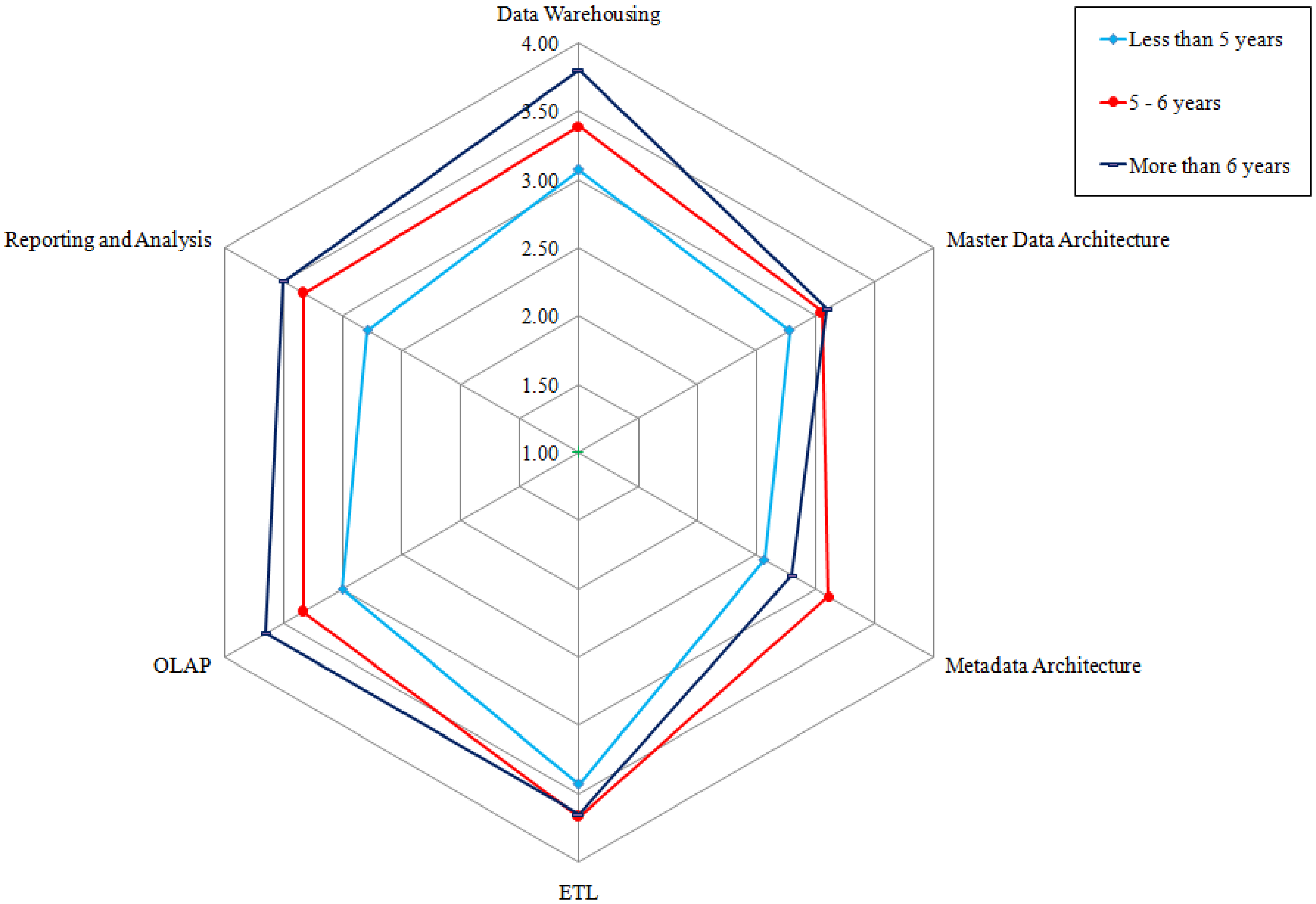


Figure 4.25: Comparative analysis of each component in the technology dimension by age of BI initiatives

In addition, BI initiatives that have existed for 5 to 6 years achieved higher maturity level (i.e., level 3) for metadata architecture component compared to the remaining two age groups. Possible reason could be that there is a lack of understanding of the importance of business metadata (Shankaranarayanan and Even, 2004).

On top of that, BI initiatives that have existed for less than 5 years scored lower maturity level (i.e., level 2) for reporting and analysis component than the remaining two age groups. This could be attributed to the cost, complexity, and learning curve of sophisticated BI tools (Eckerson, 2007b).

IV. Outcome dimension by age of BI initiatives

Table 4.29 and Figure 4.26 show the comparison of each component in the outcome dimension based on age of BI initiatives.

Table 4.29: Descriptive analysis for outcome dimension and age of BI initiatives

Component	Age of BI initiatives					
	Less than 5 years		5 – 6 years		More than 6 years	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Data quality	2.79	0.80	3.22	0.55	3.30	0.66
Information quality	2.79	0.89	3.39	0.61	3.70	0.66
KPIs	3.14	1.03	3.39	0.70	3.25	0.97

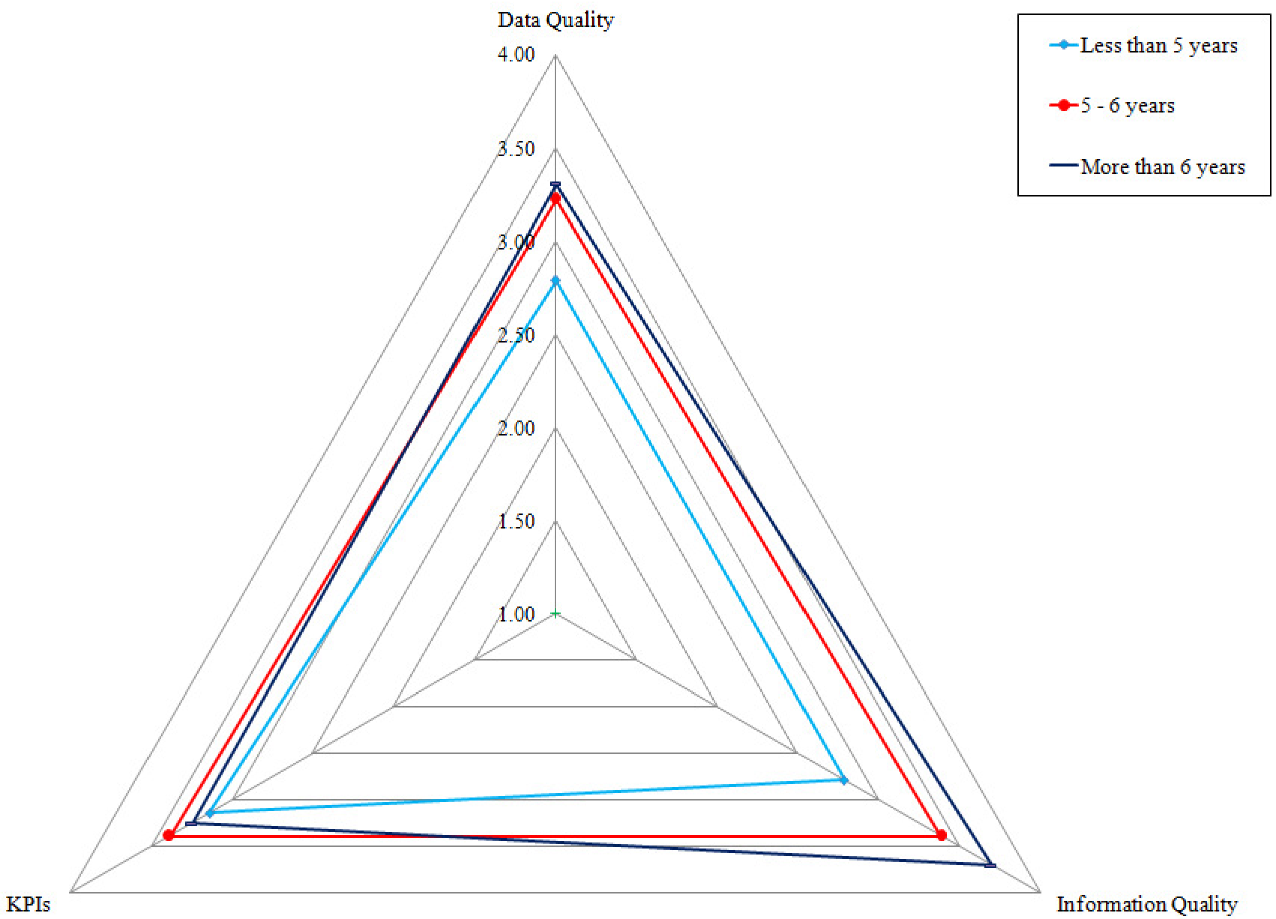


Figure 4.26: Comparative analysis of each component in the outcome dimension by age of BI initiatives

The results show that there is a gradient in maturity of data quality and information quality components among the three age groups of organizations. In particular, BI initiatives that have existed for less than 5 years received lower maturity level (i.e., level 2) compared to BI initiatives that have existed for 5 to 6 years and more than 6 years with higher maturity level (i.e., level 3).

With regard to KPIs component, all three age groups of organizations have a similar maturity level (i.e., level 3). In particular, BI initiatives that have existed for 5 to 6 years scored higher mean score of 3.39 than the remaining two age groups. This indicates that the efforts to improve organizational performance with the development of integrated KPIs.

4.4.4 Summary of Hypotheses Testing

The overall results of all the three tested hypotheses and the decision of acceptance or rejection for each hypothesis are summarized in Table 4.30.

Table 4.30: Summary of hypotheses testing and the decisions

Hypothesis		Decision
H1:	The types of industry have significant effects on the BI maturity.	**H1 has been substantiated** The findings indicated that the types of industry had significant effects on the BI maturity.
H2:	The organizational size has a significant effect on the BI maturity.	**Fail to support H2** The findings indicated that the organizational size had no significant effect on the BI maturity.
H3:	The age of BI initiatives has a significant effect on the BI maturity.	**Fail to support H3** The findings indicated that the age of BI initiatives had no significant effect on the BI maturity.

4.5 Conclusions

The survey results showed that Malaysian organizations are at level 2 (i.e., Repeatable) to level 4 (i.e., Managed) of BI maturity. However, most of the organizations have BI maturity at level 3 (i.e., Defined). The findings also revealed that the technology and outcome dimensions had highest BI maturity scores. These results implies that performing well on these two dimensions do not increase overall BI maturity. In term of comprehensiveness, organizations need to balance and coordinate their improvement activities across four dimensions (i.e., organizational management, process, technology, and outcome) so that they can attain desired level of BI maturity.

Aside from that, the results obtained from the hypotheses testing showed that among the three demographic variables (i.e. types of industry, organizational size and age of BI initiatives), only the types of industry had significant effects on the BI maturity. The results also showed that the organizations from service industries achieved higher mean score than the non-service industries, especially with respect to organizational and outcome dimensions. Service industries are very information-intensive and focus more on improving products and services for their customers. In contrast, non-service industries focus on improving processes for the production and distribution of their products and services.

CHAPTER 5

CONCLUSIONS AND FUTURE RECOMMENDATIONS

5.1 Introduction

This chapter wraps up the discussion for this research. It encompasses the following topics:

i. Overall conclusions from the research findings
ii. Research contributions
iii. Limitations and future recommendations

5.2 Overall Conclusions from The Research Findings

As described in chapter 1, the primary aim of this research is to study the BI maturity level in Malaysian organizations, and factors that affect the BI maturity. In order to achieve this aim, three research objectives were formed as following:

i. **Objective 1:** To develop and empirically test a multi-dimensional BI maturity model with distinct maturity levels and associated components that assesses the BI maturity level in Malaysian organizations.

ii. **Objective 2:** To assess the current maturity level of BI implementation in Malaysian organizations.

iii. **Objective 3:** To study the effect of demographic variables such as types of industry, organizational size, and age of BI initiatives on the level of BI maturity in Malaysian organizations.

Overall, all the research objectives have been achieved. The subsequent sub-sections summarize the findings obtained in this research.

5.2.1 Develop and Empirically Test a Multi-Dimensional BI Maturity Model with Distinct Maturity Levels and Associated Components that Assesses the BI Maturity Level in Malaysian Organizations

Many organizations have adopted BI solutions to manage various aspects of their business operations. Despite of having these solutions for years, organizations still face challenges ranging from having the right tools, skills, and processes, to important factors such as good data quality. There is a general lack of understanding on how to use BI properly for decision making and creating competitive advantage. As a result, some of them are unable to acquire the desired return on investment from BI. Therefore, BI maturity model plays a crucial role in addressing these issues by measuring and evaluating the level of BI adoption within an organization.

In this research, a multi-dimensional BI maturity model with five maturity levels (as shown in Figure 2.14) was developed using the core-ideas of capability maturity model (CMM) (Paulk et al., 1993) and TDWI's BI maturity model (Eckerson, 2007b). This so-called MOBI (Malaysian Organizations' Business Intelligence) maturity model that assesses the BI maturity level of Malaysian organizations consists of five-point scale (i.e. 1= Initial, 2= Repeatable, 3= Defined, 4= Managed, and 5= Optimizing) which corresponds to the five maturity levels of BI.

This model addressed some of the weaknesses of existing BI maturity models (e.g. Sen et al., 2006; Davenport and Harris, 2007; Eckerson, 2007b; Sacu and Spruit, 2010), such as the lack of empirical data for validation and focus on one or two specific areas (has been discussed in detail in section 2.7.11). It is believed that this BI maturity model is comprehensive enough to cover all dimensions of consideration when an organization plans to implement or expand BI. The BI maturity model could help an organization in Malaysia to categorize the state of organizations' BI capabilities and determine which areas need special attention.

As has been described in section 2.7, four main dimensions (organizational management, process, technology, and outcome) along with the associated components in each dimension had been identified through the review of extant academic and practitioner literatures. Overall, technology and outcome dimensions had achieved the highest BI maturity with average mean score of 3.25 respectively, followed by organizational management dimension with average mean score of 3.13, and lastly process dimension with average mean score of 3.00 (has been discussed in detail in section 4.3.5).

The following subsections summarise the results for each of the BI dimensions in the MOBI maturity model shown in Figure 2.14.

5.2.1.1 Organizational management

As described in section 4.3.1, there are 11 components in this dimension: Vision, Goals, Scope, BI Awareness, Strategic Alignment, Business Commitment, IT Commitment, Governance, Skills and Competencies, Training, and Sponsorship and Funding. Overall, the findings discussed in section 4.3.1.12 reveal that sponsorship and funding component received the highest average mean score (3.50). The key to a higher maturity level is to have consistent support and sponsorship from business executives. This result implies that the executive sponsors of the surveyed organizations have shown a very keen interest in supporting BI initiatives where they understand the need and potential of BI in their business .In contrast, training component attained the lowest average mean score (2.58). The study of Negash (2004) stated that training is a major contributor to high levels of BI usage. So, this result suggests that organizations need to develop a formalized BI training program and leverage BI expertise to educate end users so as to promote more widespread use of BI within the organizations.

5.2.1.2 Process

This dimension includes five components: Implementation, Change Management, Master Data Management, Metadata Management, and Data

Governance as described in section 4.3.2. Overall, the findings reported in section 4.3.2.6 show that data governance component received the highest average mean score (3.31). This result implies that the surveyed organizations aware of the importance of defining policies in every core business processes to enforce accountability for the data consumed and produced. On the contrary, change management component attained the lowest average mean score (2.77). Although surveyed organizations possess a positive attitude towards BI change, they need to define an automated enterprise-wide change management activities and best practices as BI requirements are frequently changing over time.

5.2.1.3 Technology

As described in section 4.3.3, there are a total of six components in this dimension: Data Warehousing, Master Data Architecture, Metadata Architecture, ETL, OLAP, and Reporting and Analysis. Overall, the findings reported in section 4.3.3.7 reveals that ETL component received the highest average mean score (3.66). This result implies that surveyed organizations are leveraging the functionalities provided by available ETL tools to automate data extraction, transformation, and loading processes at a faster speed of execution. Conversely, metadata architecture component attained the lowest average mean score (2.84). The findings reveal that surveyed organizations aware about the importance of capturing technical, operational, and business metadata. However, they manage these metadata separately as there is no centralized metadata architecture in place. Without well-defined metadata architecture, it could lead to ineffective administration, change control, and distribution of the data (Mhashilkar and Sarkar, 2009).

5.2.1.4 Outcome

This dimension contains three components: Data Quality, Information Quality, and KPIs as described in section 4.3.4. Overall, the findings discussed in section 4.3.4.4 reveals that information quality component received the highest average mean score (3.45). The result implies that the availability of timely and good quality information is significant for organizations to make accurate decisions and take right actions that can further business improvement. In contrast, data quality component attained the lowest average mean score (3.19). Having data cleansing tools and addressing the underlying cause for bad data could enhance the quality of usability of organizational information. In fact, these data quality activities are not adequate to ensure data are of high quality as data errors will still continue to exist after resolving. Thus, these findings suggest that proactive actions should be taken to prevent errors from occurring in the first place.

5.2.2 Assess the Current Maturity Level of BI Implementation in Malaysian Organizations

An empirical study had been conducted to investigate the current maturity level of BI implementations in Malaysian organizations. Through the literature reviews, there are no previous studies exist that examine the BI maturity issues in Malaysia. The findings discussed in section 4.3.5 reveal that the average mean score of the overall BI maturity is 3.16. The findings also indicate that 52 percent of surveyed organizations are positioned at level 2 (i.e. Repeatable) to level 4 (i.e. Managed) of BI maturity. This reflects that the Malaysian organizations are still at moderate level of BI maturity and have not fully obtained all the potential benefits from their BI investments. Not surprisingly, the findings also show that no organizations have achieved the highest level of maturity. This implies that there are still rooms of improvements where organizations can and should move up the maturity hierarchy so that they can gauge all potential benefits of BI.

5.2.3 Study the Effect of Demographic Variables such as Types of Industry, Organizational Size, and Age of BI Initiatives on the BI Maturity

This research had attested the hypotheses formed at the early stage of this research through the hypotheses testing. Through literature reviews, it is found that little research had been done in previous studies on effect of demographic variables (i.e. types of industry, organizational size, and age of initiatives) on the BI maturity. As described in chapter 3, the independent-samples t-test was used to examine whether or not the types of industry have significant effects on the BI maturity, whereas one-way ANOVA test was used to investigate whether or not the organizational size and age of BI initiatives have significant effects on the BI maturity.

The results obtained from the hypotheses testing of H1 to H3 (as discussed in section 4.4.1 to 4.4.3) showed that demographic variable such as types of industry had significant effects on the BI maturity, whereas the organizational size and age of BI initiatives did not have. Driven by increased data growth, BI is designed to fit all needs regardless of organizational size and no longer a technology that can be deployed by large organizations. Small- and medium organizations are affordable to invest in a diversity of BI and analytical solutions to acquire BI capabilities. The results shown in Table 4.12 indicated that the organizations from service industries achieved higher mean score than the non-service industries. Furthermore, it was found that service industries have a strong emphasis on technology and outcome dimensions while non-service industries focus more on technology and organizational dimensions. This could be attributed to the difference in quality improvement strategies.

5.3 Research Contributions

The development and validation of a multi-dimensional BI maturity model in this research provide a significant contribution to the body of knowledge in the area of management of BI initiative. Specifically, this maturity model overcomes the limitations of existing BI maturity models that mainly focus on one or two specific areas. Besides, the findings of this research add to the contextual understanding of BI maturity and the key dimensions deemed important for the success of BI implementation. Such an understanding can help the Malaysian organizations to analyze their BI from various perspectives.

Although some studies of BI maturity have been made in other countries, there are no previous studies exist that investigate the maturity issues of BI in Malaysia from reviewing the extant literature so far. The scope of this research is novel in the Malaysian context. So, it serves to be a good pilot project in this area and a foundation for future research in the BI related area. It is believed that the research findings could be used as guideline for organizations adopting BI, especially in Malaysia to better identify their current BI state and start balancing all the aspects and take actions towards achieving the desired maturity level, thereby enabling continuous business growth in the future. By looking at the BI maturity radar chart, the BI stakeholders can identify the components that require more attention and which area the organization is already achieving well. The result of this research highlights those BI dimensions and components that need to be addressed and given particular attention in order to move up to a higher level.

In addition, the research findings pertaining to the effects of demographic variables on BI maturity could provide useful information to assist future researchers on the design of BI maturity models. Besides, analysis of demographic factors could contribute to enhancing organizations' understanding of BI in varying contexts, and thus leading to more effective BI investments.

5.4 Limitations and Recommendations

While this research has developed and attested the efficacy of a BI maturity model, the results presented in chapter 4 have to be interpreted with some limitations in mind. Besides that, this section also suggests relevant recommendations to resolve the limitations found in this research for future research.

First, the sample sizes are not representative of all Malaysian organizations. From the 148 questionnaires distributed, only a total of 52 completed questionnaires were returned due to the issue of confidentiality. This correlates to a response rate of 35.1 percent. In other words, these limited sample sizes may not possible to generalize the findings that have been obtained from this research. In addition, these sample sizes also limit the data analysis techniques (e.g. factor analysis) applied to the data collected. So, it is suggested that larger sample sizes could be used in further research to increase the power of generalizing results as well as establish the comprehensiveness and validity of this maturity model. Additionally, as this research is focused on Malaysia only, it is recommended to conduct the research in different geographical area. Wider geographical area helps to gain a more comprehensive understanding towards BI maturity levels.

Another limitation of this research is the cross-sectional nature of the data collected due to the limited resources and time. Although this BI maturity model is supported by empirical data, theoretical assumptions, and previous research findings, further research can extend existing work by conducting longitudinal and experimental studies to examine the changes of BI maturity of an organization over time. Such studies are useful and can serve as benchmarks to Malaysian organizations that plan to improve BI.

A higher level of maturity in BI initiatives is essential for an organization to gain full benefits of BI. However, it is extremely difficult for an organization to move up the maturity ladder of BI. In this research, scope of study focuses only on the survey assessment of the BI maturity level of Malaysian organizations based on the BI maturity model and the effects of demographic variables to the BI maturity level of the organization. Further work can be carried out by formulating strategies or methodology to help organizations in Malaysia to move up maturity level to overcome difficulty. Besides that, future research can revise the BI maturity components based on experiences in practice as well as validate the detailed relationship between BI dimensions and components.

5.5 Conclusions

This chapter has outlined the overall conclusions, contributions, limitations, recommendations for future studies. This research bridged the research gap that exists between academic and practitioners by developing a multi-dimensional BI maturity model. It is hoped that synthesizing different dimensions of BI maturity into a comprehensive BI maturity model could assist organizations to focus their BI improvement efforts on the critical components that lead to enhanced overall BI maturity.

From the findings obtained in this research, there were indications that:

- A multi-dimensional BI maturity model with five maturity levels was developed by using the core-ideas of capability maturity model (CMM) and TDWI's BI maturity model to provide insights into the strengths and weaknesses of organizations in managing their BI initiatives.
- Malaysian organizations were performing well in term of technology and outcome dimensions but they need to put more efforts on organizational management and process dimensions.
- Malaysian organizations are still at moderate level of BI maturity and have not yet reached the highest level of BI maturity.
- Types of industry had significant effects on the BI maturity in Malaysia.

REFERENCES

Ahern, D.M., Clouse, A. and Turner, R., 2004. *CMMI distilled: A practical introduction to integrated process improvement*, 2nd ed. London: Addison-Wesley.

Aho, M., 2009. A capability maturity model for corporate performance management - an empirical study in large Finnish manufacturing companies. *Proceedings of the e-Business Research Forum 2009 - Research Forum to Understand Business in Knowledge Society*, 23-25 September 2009 Jyväskylä, Finland. Tampere: Tampere University of Technology and University of Jyväskylä, pp. 1 – 20.

Arnott, D. and Pervan, G., 2005. A critical analysis of decision support systems research. *Journal of Information Technology*, 20 (2), pp. 67 – 87.

Atre, S., 2003, *The top 10 critical challenges for business intelligence success* [Online]. Available at: http://www.computerworld.com/computerworld/records /images/pdf/BusIntell WPonline.pdf [Accessed: 13 September 2013].

AusIndustry, 1999. *Key performance indicators manual: A practical guide for the best practice development, implementation and use of KPIs*. New South Wales: Allen & Unwin.

Auth, G. and von Maur, E., 2002. A software architecture for XML-based metadata interchange in data warehouse systems. In: Chaudhri, A.B., Unland, R., Djeraba, C. and Lindner, W. (eds.). *XML-Based Data Management and Multimedia Engineering – EDBT 2002 Workshops*. Czech Republic: Springer Berlin Heidelberg, pp. 1 – 14.

Azvine, B., Cui, Z., Nauck, D.D. and Majeed, B., 2006. Real time business intelligence for the adaptive enterprise. *Proceedings of the 8th IEEE International Conference on E-Commerce Technology and the 3rd IEEE International Conference on Enterprise Computing, E-Commerce, and E-Services*, 26-29 June 2006 San Francisco, CA. Washington: IEEE Computer Society, pp. 29 – 39 .

Bank Rakyat, 2002, *Malaysia-based Bank Rakyat employs MicroStrategy's business intelligence platform* [Online]. Available at: http://www.micro strategy.com/news/pr_system/pressrelease.asp?ctry=167&id=849 [Accessed: 12 March 2012].

Baskarada, S., Koronios, A. and Gao, J., 2007. IQM-CMM: A framework for assessing organizational information quality management capability maturity. *Proceedings of the 12th International Conference on Information Quality*, 9-11 November 2007 Cambridge, Massachusetts. Cambridge: MIT Press, pp. 317 – 332.

Bates, C. and Wall, C., 2012, *Top six BI trends for 2012* [Online]. Available at: http://www.cio.com.au/article/421700/top_six_bi_trends_2012/ [Accessed: 12 March 2013].

Berson, A. and Dubov, L., 2010. *Master data management and data governance*, 2nd ed. New York: McGraw-Hill.

Boone Jr., H.N. and Boone, D.A., 2012. Analyzing Likert Data. *Journal of Extension*, 50 (2), pp. 1 – 5.

Bryan, C., 2009, *Quick guide to implementing business intelligence, data warehousing & BPM* [Online]. Available at: http://ezinearticles.com/?Quick-Guide-to-Implementing-Business-Intelligence,-Data-Warehousing-and-BPM&id=3465076 [Accessed: 5 December 2012].

Bryman, A., 2012. *Social research methods*, 4th ed. New York: Oxford University Press.

Burns, M., 2005, Business intelligence survey [Online]. Available at: http://www.camagazine.com/archives/print-edition/2005/june-july/columns/camagazine19684.aspx [Accessed: 12 December 2012].

Canes, M., 2009, *Business intelligence for the SME* [Online]. Available at: http://www.bluelinkerp.com/downloads/2009-10-15-Business-Intelligence-for-the-SME.pdf [Accessed: 12 December 2012].

Cates, J.E., Gill, S.S. and Zeituny, N., 2005. The ladder of business intelligence (LOBI): A framework for enterprise IT planning and architecture. *International Journal of Business Information Systems*, 1 (1-2), pp. 220 – 238.

Chung, W., Chen, H. and Nunamaker Jr., J.F., 2003. Business intelligence explorer: A knowledge map framework for discovering business intelligence on the Web. *Proceedings of the 36th Annual Hawaii International Conference on System Sciences*, 6-9 January 2003 Hawaii, USA. Los Alamitos: IEEE Computer Society, pp. 1 – 10.

Chung, W., Hsinchun, C. and Nunamaker Jr, J.F., 2005. A visual framework for knowledge discovery on the Web: An empirical study of business intelligence exploration. *Journal of Management Information Systems*, 21 (4), pp. 57 – 84.

Cortina, J., 1993. What is coefficient alpha: An examination of theory and applications. *Journal of Applied Psychology*, 78 (1), pp. 98 – 104.

Creswell, J.W., 2013. *Research design: Qualitative, quantitative and mixed methods approaches*, 4th ed. California: Sage Publications.

Davenport, T.H., 2006. Competing on analytics. *Harvard Business Review*, 84 (1), pp. 98 – 107.

Davenport, T.H. and Harris, J.G., 2007. *Competing on analytics: The new science of winning*. Boston: Harvard Business School Press.

David, M. and Sutton, C.D., 2011. *Social research: An introduction*, 2nd ed. London: Sage Publications.

Dayal, U., Castellanos, M., Simitsis, A. and Wilkinson, K., 2009. Data integration flows for business intelligence. *Proceedings of the 12th International Conference on Extending Database Technology: Advances in Database Technology*. 24-26 March 2009 Saint Petersburg, Russia. New York: ACM, pp. 1 – 11.

de Bruin, T. and Rosemann, M., 2005. Towards a business process management maturity model. *Proceedings of the 13th European Conference on Information Systems*, 26-28 May 2005. Regensburg: ECIS, pp. 521 – 532.

de Bruin, T., Rosemann, M., Freeze, R. and Kulkarni, U., 2005. Understanding the main phases of developing a maturity assessment model. *Proceedings of the 6th Australasian Conference on Information Systems*, 29 November-2 December 2005 Sydney, Australia. Sydney: Queensland University of Technology, pp. 1 – 10.

Dekkers, J., Versendaal, J. and Batenburg, R., 2007. Organising for business intelligence: A framework for aligning the use and development of information. *Proceedings of the 20th Bled eConference eMergence: Merging and Emerging Technologies, Processes, and Institutions*, 4-6 June 2007 Bled, Slovenia. USA: Association for Information Systems, pp. 1 – 15.

DeGeneres, B., 2008, *Valuing business intelligence* [Online]. Available at: http://www.wellslanders.com/documents/Valuing%20BI%20v4.pdf [Accessed: 16 December 2012].

DiGi, 2009, *Malaysian mobile firm invests in BI solution* [Online]. Available at: http://mis-asia.com/news/articles/malaysian-mobile-firm-invests-in-bi-solu tion [Accessed: 12 December 2012].

Dresner, H., 2010, *Wisdom of crowds business intelligence market study* [Online]. Availabe at: http://manitex.ie/pdf/Dresner_Report_2010.pdf [Accessed: 12 December 2012].

Dyche, J. and Levy, E., 2009, *The baseline on MDM: Five levels of maturity for master data management* [Online]. Available at: http://download.101 com.com/tdwi/ww29/Baseline_The_Baseline_on_MDM.pdf [Accessed: 12 December 2012].

Eckerson, W.W., 2003, *Smart companies in the 21st century: The secrets of creating successful business intelligence solutions* [Online]. Available at: http://download.101com.com/tdwi/research_report/2003BIReport_v7.pdf [Accessed: 12 December 2012].

Eckerson, W.W., 2004, *In search of a single version of truth: Strategies for consolidating analytic silos* [Online]. Available at: http://www.mahmoud youssef.com/BI/8.pdf [Accessed: 12 December 2012].

Eckerson, W.W., 2007a, *TDWI BI benchmark report* [Online]. Available at: http://tdwi.org/~/media/86FE9B6DA255431C84E20570BBFFF3EB.pdf [Accessed: 24 December 2012].

Eckerson, W.W., 2007b, *Beyond the basics: Accelerating BI maturity* [Online]. Available at: http://download.101com.com/pub/tdwi/Files/SAP_monograph _0407.pdf [Accessed: 8 March 2012].

Eckerson, W.W., 2008, *Pervasive business intelligence: Techniques and technologies to deploy on an enterprise scale* [Online]. Available at: http://www.umsl.edu/~sauterv/DSS4BI/links/pdf/BI/pervasiveBI.sas.pdf [Accessed: 12 December 2012].

Elbashir, M.Z., Collier, P.A. and Davern, M.J., 2008. Measuring the effects of business intelligence systems: The relationship between business process and organizational performance. *International Journal of Accounting Information Systems*, 9 (3), pp. 135 – 153.

Elbashir, M.Z., Collier, P.A. and Sutton, S.G., 2011. The role of organizational absorptive capacity in strategic use of business intelligence to support integrated management control systems. *The Accounting Review*, 86 (1), pp. 155 – 184.

English, L.P., 2005, *Business intelligence defined* [Online]. Available at: http://www.b-eye-network.com/view/1119 [Accessed: 16 December 2012].

Evelson, B., 2010, *Bottom up and top down approaches to estimating costs for a single BI report* [Online]. Available at: http://blogs.forrester.com/business_process/2010/01/bottom-up-and-top-down-approaches-to-estimating-cost-for-a-single-bi-report.html [Accessed: 21 December 2012].

Evelson, B., 2012, *Top 10 BI predictions for 2013 and beyond* [Online]. Available at: http://blogs.forrester.com/boris_evelson/12-12-12-top_10_bi_predictions_for_2013_and_beyond [Accessed: 11 January 2013].

Fisher, D.M., 2004, *The business process maturity model: A practical approach for identifying opportunities for optimization* [Online]. Available at: http://www.bptrends.com/publicationfiles/10-04%20ART%20BP%20Maturity%20Model%20-%20Fisher.pdf [Accessed: 21 December 2012].

Foley, E. and Manon, G., 2010. What is business intelligence? *International Journal of Business Intelligence Research*, 1 (4), pp. 1 – 28.

Forza, C., 2002. Survey research in operations management: A process-based perspective. *International Journal of Operations & Production Management*, 22 (2), pp. 152 – 194.

Frolick, M.N. and Ariyachandra, T.R., 2006. Business performance management: One truth. *Information Systems Management*, 23 (1), pp.41 – 48.

Gangadharan, G.R. and Swami, S.N., 2004. Business intelligence systems: Design and implementation strategies. *Proceedings of the 26th International Conference Information Technology Interfaces*, 7-10 June 2004 Cavtat, Croatia. Cavtat: IEEE Xplore, pp. 139 – 144.

Gartner, 2004. *Using business intelligence to gain a competitive edge*. Stamford: Gartner.

Gartner, 2013, *Gartner says worldwide business intelligence software revenue to grow 7 percent in 2013* [Online]. Available at: http://www.gartner.com/newsroom/id/2340216 [Accessed: 13 March 2013].

Genting, 2010, *Betting on the dice* [Online]. Available at: http://www.sas.com/success/rwb.html [Accessed: 12 December 2012].

Ghauri, P. and Gronhaug, K., 2005. *Research methods in business studies: A practical guide*, 3rd ed. Harlow: Prentice Hall.

Ghosh, T., 2011. Impact of order of entry on firm performance: Comparison between service and manufacturing firms in an Indian context. *Romanian Journal of Marketing*, 4, pp.9 – 22.

Glancy, F.H. and Yadav, S.B., 2011. Business intelligence conceptual model. *International Journal of Business Intelligence Research*, 2(2), pp. 48 – 66.

Goetz, M., 2013, Data governance will shine in the data economy [Online]. Available at: http://www.kmworld.com/Articles/Editorial/Features/Data-governance-will-shine-in-the-Data-Economy-90500.aspx [Accessed: 12 December 2012].

Golfarelli, M., Rizzi, S. and Cella, I., 2004. Beyond data warehousing: What's next in business intelligence? *Proceedings of the 7th ACM international workshop on Data warehousing and OLAP*, 12-13 November 2004 Washington, USA. New York: ACM, pp. 1 – 6.

Gottschalk, P., 2009. Maturity levels for interoperability in digital government. *Government Information Quaterly*, 26 (1), pp. 75 – 81.

Gottschalk, P. and Solli-Saether, H., 2010. Computer information systems in financial crime investigations. *The Journal of Computer Information Systems*, 50 (3), pp. 41 – 49.

Guarda, T., Santos, M., Pinto, F., Augusto, M. and Silva, C., 2013. Business intelligence as a competitive advantage for SMEs. *International Journal of Trade, Economics and Finance*, 4 (4), pp.187 – 190.

Gunter, D.M., 2007, *Build the right business intelligence plan: A management's guide to creating a plan that maximizes your return on business intelligence* [Online]. Available at: http://optimizeyoursupplychain.com/docs/bi/ePartnersBI_WP.pdf [Accessed: 12 March 2013].

Haag, S., Cummings, M. and Philips, A., 2007. *Management information systems for the information age*, 6th ed. Boston: McGraw-Hill.

Hair, J.F. and Anderson, R.E., 2010. *Multivariate data analysis*, 7th ed. Upper Saddle River: Prentice Hall.

Hawking, P. and Sellitto, C., 2010. Business intelligence (BI) critical success factors. *Proceedings of the 21st Australasian Conference on Information Systems*, 1-3 December 2010 Brisbane, Australia. Brisbane: ACIS, pp. 1 – 10.

HP, 2007, *Managing data as a corporate asset: Three action steps toward successful data governance* [Online]. Available at: http://img.itcpn.net/imagelist/2007/130/8h3a2j1h8s50.pdf [Accessed: 11 April 2013].

HP, 2012, *Describing the BI journey: The HP business intelligence maturity model* [Online]. Available at: http://www8.hp.com/h20195/v2/GetDocument.aspx?docname=4AA3-9723ENW [Accessed: 12 March 2013].

Heyns, H., Gallagher, S. and Trautwein, B., 2009, *Does your business intelligence tell you the whole story* [Online]. Available at: http://www.kpmg.com/UK/en/IssuesAndInsights/ArticlesPublications/Documents/PDF/Advisory/146307_BI_POINT_OF_VIEW_FINAL.pdf [Accessed: 8 May 2013].

Hill, R., 1998. What sample size is "enough" in Internet survey research. *Interpersonal Computing and Technology: An Electronic Journal for the 21st Century*, 6 (3-4), pp. 1 – 10.

Hinton, P.R., 2014. *Statistics explained*, 3rd ed. Hove: Routledge.

Hostmann, B., 2007, *BI competency centers: Bringing intelligence to the business* [Online]. Available at: http://businessfinancemag.com/business-performance-management/bi-competency-centers-bringing-intelligence-business [Accessed: 8 May 2013].

Howson, C., 2008. *Successful business intelligence: Secrets to making BI a killer app*. New York: McGraw-Hill.

IBM, 2007, *Master data management: Looking beyond the single view to find the right view* [Online]. Available at: http://www-935.ibm.com/services/nz/cio/pdf/leverage_wp_mdm_beyond_single_view.pdf [Accessed: 11 June 2013].

IDG Enterprise, 2013, *CIO magazine tech poll/tech priorities survey* [Online]. Available at: http://www.cio.com/documents/pdfs/CIOTechPrioritiesFeb2013.pdf [Accessed: 11 August 2013].

Inland, 2010, *Malaysia's Inland revenue board gets clearer picture of taxpayers with SAS* [Online]. Available at: http://www.sas.com/success/mirb.html [Accessed: 31 October 2012].

ISM, 2010, *ISM empowers insurance industry with SAS* [Online]. Available at: http://www.sas.com/success/ism.html [Accessed: 31 October 2012].

Iversen, J., Nielsen, P.A. and Norbjerg, J., 1999. Situated assessment of problems in software development. *Database for Advances in Information Systems*, 30 (2), pp. 66 – 81.

Johnson, B. and Christensen, L., 2012. *Educational research: Quantitative, qualitative, and mixed approaches*, 4th ed. Thousand Oaks, Sage Publications.

Jourdan, Z., Rainer, R.K. and Marshall, T.E., 2008. Business intelligence: An analysis of the literature. *Information Systems Management*, 25 (2), pp. 121 – 131.

Klein, H.K. and Myers, M.D., 1999. A set of principles for evaluating and conducting interpretive field studies in information systems. *MIS Quarterly*, 23 (1), pp. 67 – 94.

Klimko, G., 2001. Knowledge management and maturity models: Building common understanding. *Proceedings of the 2nd European Conference on Knowledge Management*, 8-9 November 2001 Bled, Slovenia. UK: MCIL Reading University Press, pp. 269 – 278.

Lahrmann, G. and Marx, F., 2010. Systematization of maturity model extensions. *Proceedings of the 5th International Conference on Global Perspectives on Design Science Research*, 4-5 June 2010 St. Gallen, Switzerland. Berlin: Springer-Verlag, pp. 522 – 525.

Larson, B., 2012. *Delivering business intelligence with Microsoft SQL server 2012*, 3rd ed. New York: McGraw-Hill.

Levy, Y. and Ellis, T.J., 2006. A systems approach to conduct an effective literature review in support of information systems research. *Informing Science Journal*, 9, pp. 181 – 212.

Levy, M. and Powell, P., 2004. *Strategies for growth in SMEs: The role of information and information systems*, 1st ed. Oxford: Butterworth-Heinemann.

Lipton, M., 1996. Demystifying the development of an organizational vision. *Sloan Management Review*, 37 (4), pp. 83 – 92.

Lönnqvist, A. and Pirttimäki, V., 2006. The measurement of business intelligence. *Information Systems Management*, 23, pp. 32 – 40.

Loshin, D., 2007, *MDM components and the maturity model* [Online]. Available at: http://www.knowledge-integrity.com/Assets/MDMComponents MaturityModel.pdf [Accessed: 31 October 2012].

Luftman, J.N., 2000. Assessing business-alignment maturity. *Communications of the Association for Information Systems*, 4 (14), pp. 1 – 50.

Luftman, J. and Ben-Zvi, T., 2010. Key issues for IT executives 2010: Judicious IT investments continue post-recession. *MIS Quartely Executive*, 9 (4), pp. 263 – 273.

Luhn, H.P., 1958. A business intelligence system. *IBM Journal of Research and Development*, 2 (4), pp. 314 – 319.

Lund, T., 2005. The qualitative-quantitative distinction: Some comments. *Scandinavian Journal of Educational Research*, 49 (2), pp. 115 – 132.

Lungu, I.C. and Bâra, A., 2005. Executive information systems development lifecycle. *Economy Informatics Review*, 1-4, pp. 19 – 22.

Malladi, S., 2013. Adoption of business intelligence & analytics in organizations – an empirical study of antecedents. *Proceedings of the 19th Americas Conference on Information Systems*, 15-17 August 2013 Chicago, Illinois. USA: Association for Information Systems, pp. 1 – 11.

Manjunath, T.N., Ravindra, S.H. and Ravikumar, G.K., 2011. Analysis of data quality aspects in data warehouse systems. *International Journal of Computer Science and Information Technologies*, 2 (1), pp.477 – 485.

March, S.T. and Hevner, A.R., 2007. Integrated decision support systems: A data warehousing perspective. *Decision Support Systems*, 43, pp. 1031 – 1043.

Marjanovic, O, 2007. The next stage of operational business intelligence: Creating new challenges for business process management. *Proceedings of the 40th Hawaii International Conference on System Sciences*, 3-6 January 2007 Waikoloa, Hawaii. Washington: IEEE Computer Society, pp. 215 – 224.

Masayna, V., Koronios, A., Gao, J. and Gendron, M., 2007. Data quality and KPI's: A link to be established. *Proceedings of the 2nd World Congress on Engineering Asset Management and the 4th International Conference on Condition Monitoring*, 11 June 2007 Harrogate, UK. Oxfordshire: Coxmoor Publishing, pp. 1376 – 1386.

McMillan, J.H. and Schumacher, S., 2003. *Research in education: A conceptual introduction*, 5th ed. New York: Pearson.

Mhashilkar, K. and Sarkar, J., 2009, Information integration: Metadata management landscape [Online]. Available at: http://databaser.net/moniwiki/pds/_eb_a9_94_ed_83_80_eb_8d_b0_ec_9d_b4_ed_84_b0_ec_9d_98_ec_a4_91_eb_8c_80_ed_95_9c_ec_97_ad_ed_95_a0/tata.pdf [Accessed: 15 May 2013].

Miller, D., 2007, *Measuring BI success: Business goals and business requirements* [Online]. Available at: http://www.information-management.com/news/10000100-1.html [Accessed: 15 May 2013].

Mingers, J., 2001. Combining IS research methods: Towards a pluralist methodology. *Information Systems Research*, 12 (3), pp. 240 – 259.

Mitchell, M.L. and Jolley, J.M., 2013. *Research design explained*, 8th ed. Belmont: Wadsworth.

Muijs, D., 2010. *Doing quantitative research in education with SPSS*, 2nd ed. Great Britain: SAGE.

Myers, M.D., 1997. Qualitative research in information systems. *MIS Quarterly*, 21 (2), pp. 241 – 242.

Myers, M.D., 2013. *Qualitative research in business and management*, 2nd ed. Los Angeles: Sage Publications.

Myers, M.D. and Avison, D., 2002. *Qualitative research in information systems: A reader introducing qualitative methods series*, 1st ed. London: Sage Publications.

Negash, S., 2004. Business intelligence. *Communications of the Association for Information Systems*, 13, pp. 177 – 195.

Negash, S. and Gray, P. 2003. Business intelligence. *Proceedings of the 9th Americas Conference on Information Systems*, 4-6 August 2003 Tampa, Florida. Tampa: AMCIS, pp. 3190 – 3199.

Neuman, W.L., 2011. *Social research methods: Qualitative and quantitative approaches*, 4th ed. Boston: Allyn & Bacon.

Olbrich, S., Poppelbuß, J. and Niehaves, B., 2012. Critical contextual success factors for business intelligence: A Delphi study on their relevance, variability, and controllability. *Proceedings of the 45th Hawaii International Conference on System Science*, 4-7 January 2012 Maui, Hawaii. Washington: IEEE Computer Society, pp. 4148 – 4157.

Olszak, C.M. and Ziemba, E., 2007. Approach to building and implementing Business intelligence systems. *Interdisciplinary Journal of Information, Knowledge, and Management*, 2, pp. 135 – 148.

Orlikowski, W.J. and Baroudi, J.J., 1991. Studying information technology in organizations: Research approaches and assumptions. *Information Systems Research*, 2 (1), pp. 1 – 8.

Hornby, A.S., 2010. *Oxford Advanced Learner's Dictionary*, 8th ed. Oxford: Oxford University Press.

Panian, Z., 2010. Some practical experiences in data governance. *World Academy of Science, Engineering and Technology*, 62, pp. 939 – 946.

Pant, P., 2009a, *Business intelligence (BI): How to build successful BI strategy* [Online]. Available at: http://www.deloitte.com/assets/Dcom-SouthAfrica/Local%20Assets/Documents/Business%20intelligence%20that%20aligns%20with%20enterprise%20goals.pdf [Accessed: 21 January 2013].

Pant, P., 2009b, *Essential components of a successful BI strategy* [Online]. Available at: http://www.information-management.com/specialreports/2009_155/business_intelligence_bi-10015846-1.html?pg=1 [Accessed: 21 January 2013].

Pareek, D., 2007. *Business intelligence for telecommunications*, 1st ed. Boca Raton: Auerbach Publications.

Paulk, M.C., Curtis, B., Chrissis, M.B. and Weber, C.V., 1993. Capability maturity model, version 1.1. *IEEE Software*, 10 (4), pp. 18 – 27.

Petrini, M. and Pozzebon, M., 2009. Managing sustainability with the support of business intelligence: Integrating socio-environmental indicators and organisational context. *Journal of Strategic Information Systems*, 18 (4), pp. 178 – 191.

Pirttimäki, V.H., 2007. Conceptual analysis of business intelligence. *South African Journal of Information Management*, 9 (2), pp. 1 – 17.

Power, D.J., 2002. *Decision support systems: Concepts and resources for managers*, 1st ed. Westport: Greenwood Publishing Group.

Power, D.J., 2007, *A brief history of decision support systems* [Online]. Available at: http://dssresources.com/history/dsshistoryv28.html [Accessed: 12 April 2013].

Prosci, 2004, *Prosci's change management maturity model* [Online]. Available at: http://www.change-management.com/prosci-cm-maturity-model-writeup.pdf [Accessed: 12 April 2013].

Prouty, K. and Castellina, N., 2011, *ERP in manufacturing 2011: Defining the ERP strategy* [Online]. Available at: http://www.flexctp.com/images/documents/ERP_in_Manufacturing_2011.pdf [Accessed: 12 March 2013].

Raber, D., Winter, R. and Wortmann, F., 2012. Using quantitative analyses to construct a capability maturity model for business intelligence. *Proceedings of the 45th Hawaii International Conference on System Sciences*, 4-7 January 2012 Wailea, Hawaii. Wailea: IEEE Computer Society, pp. 4219 – 4228.

Raber, D., Wortmann, F. and Winter, R., 2013. Situational business intelligence maturity models: An exploratory analysis. *Proceedings of the 46th Hawaii International Conference on System Sciences*, 7-10 January 2013 Wailea, Hawaii. Wailea: IEEE Computer Society, pp. 3797 – 3806.

Radcliffe, J., 2007, *The seven building blocks of MDM: A Framework for success* [Online]. Available at: http://www.gartnerinfo.com/mdm2/TheSevenBuildingBlocksofMDMAFrameworkforSuccess.pdf [Accessed: 12 March 2013].

Ramamurthy, K., Sen, A. and Sinha, A.P., 2008. An empirical investigation of the key determinants of data warehouse adoption. *Decision Support Systems*, 44 (4), pp. 817 – 841.

Ramanigopal, C.S., Palaniappan, G. and Joy, P.A., 2012. Business intelligence for competence in financial services. *International Journal of Research in Finance and Marketing*, 2 (6), pp. 1 – 17.

Ranjan, J., 2008. Business justification with business intelligence. *VINE: The Journal of Information and Knowledge Management Systems*, 38 (4), pp. 461 – 475.

Rasmussen, N.H., Bansal, M. and Chen, C.Y., 2009. *Business dashboards: A visual catalog for design and deployment*, 1st ed. Hoboken: John Wiley & Sons.

Realmild, 2009. *Radicare focuses on opportunities in the Middle East* [Online]. Available at: http://www.mida.gov.my/en_v2/index.php?mact=News,cntnt01,detail,0&cntnt01articleid=528&cntnt01returnid=388 [Accessed: 21 January 2013].

Rehani, B., 2011. Agile way of BI implementation. *2011 Annual IEEE India Conference*, 16-18 December 2011 Hyderabad, India. Hyderabad: IEEE Computer Society, pp. 1 – 6.

Reinschmidt, J. and Francoise, A., 2000. *Business intelligence certification guide*, 1st ed. San Jose: Vervante.

Ricoh, 2010, *Ricoh Malaysia takes next step to 'total business intelligence'* [Online]. Available at: http://mis-asia.com/news/articles/ricoh-malaysia-takes-next-step-to-total-business-intelligence [Accessed: 21 January 2013].

Riley, J.A. and Delic, K.A., 2010. Enterprise knowledge clouds: Applications and solutions. In: Furht, B. and Escalante, A. (eds.). *Handbook of Cloud Computing*. New York: Springer, pp. 437 – 452.

Roscoe, J.T., 1975. *Fundamental research statistics for behavioral science*, 2nd ed. New York: Holt, Rinehart and Winston.

Russell, S., Haddad, M., Bruni, M. and Granger, M., 2010. Organic evolution and the capability maturity of business intelligence. *Proceedings of the 16th Americas Conference on Information Systems*, 12-15 August 2010 Lima, Peru. Lima: AMCIS, pp. 4271 – 4280.

Ryu K., Park, J. and Park, J., 2006. A data quality management maturity model. *ETRI Journal*, 28 (2), pp. 191 – 204.

Sabherwal, R. and Becerra-Fernandez, I., 2009. *Business intelligence: Practices, technologies, and management*. Hoboken: John Wiley and Sons.

Sacu, C. and Spruit, M., 2010. BIDM: The business intelligence development model. *Proceedings of the 12th International Conference on Enterprise Information Systems*, 8-12 June 2010 Funchal, Madeira. Lisboa: SciTePress, pp. 288 – 293.

Sallam, R.L., Hostmann, B., Richardson, J. and Bitterer, A., 2010, *Magic quadrant for business intelligence platforms* [Online]. Available at: http://www.gartner.com/technology/media-products/reprints/oracle/article121/article121.html [Accessed: 21 January 2013].

SAS, 2008, *Business intelligence maturity and the quest for better performance* [Online]. Available at: http://www.sas.com/resources/whitepaper/wp_3511.pdf [Accessed: 21 January 2013].

SAS, 2014, *SAS Malaysia records strong business growth, surpassing RM49.1Million in 2013 revenue* [Online]. Available at: http://www.sas.com/en_my/news/press-releases/2014/march/SAS-Malaysia-records-strong-business-growth-in-2013.html [Accessed: 25 May 2014].

Saunders, M., Lewis, P. and Thornhill, A., 2012. *Research methods for business students*, 6th ed. Harlow: Pearson.

Sayyadi, M., Farazmand, E. and Gholami, O., 2012. Business intelligence maturity model in organization on the base of the capability maturing model (CMM). *The Journal of Mathematics and Computer Science*, 4 (2), pp. 110 – 119.

Senheng, 2010, *Reaping from biz intelligence* [Online]. Available at: http://www.senheng.com.my/news_corporate_show.asp?id=347&catName=Archive+2007 [Accessed: 21 January 2013].

Sen, A., Ramamurthy, K. and Sinha, A.P., 2012. A model of data warehousing process maturity. *IEEE Transactions on Software Engineering*, 38 (2), pp. 336 – 353.

Sen, A., Sinha, A.P. and Ramamurthy, K., 2006. Data warehousing process maturity: An exploratory study of factors influencing user perceptions. *IEEE Transactions on Engineering Management*, 53 (3), pp. 440 – 455.

Shankaranarayanan, G. and Even, A., 2004. Managing metadata in data warehouses: Pitfalls and possibilities. *Communications of the Association for Information Systems*, 14, pp. 247 – 274.

Shanks, G., Bekmamedova, N., Adam, F. and Daly, M., 2012. Embedding business intelligence systems within organisations. In: Respicio, A. and Burstein, F. (eds.). *Fusing Decision Support Systems into the Fabric of the Context*. Netherlands: IOS Press, pp. 113 – 124.

Shariat, M. and Hightower Jr, R., 2007. Conceptualizing business intelligence architecture. *Marketing Management Journal*, 17 (2), pp. 40 – 46.

Shi, Z. et al., 2007. MSMiner - a developing platform for OLAP. *Decision Support Systems*, 42 (4), pp. 2016 – 2028.

Shim, J.P. et al., 2002. Past, present, and future of decision support technology. *Decision Support Systems*, 33 (2), pp. 111 – 126.

Shollo, A. and Kautz, K., 2010. Towards an understanding of business intelligence. *Proceedings of the 21st Australasian Conference on Information Systems*, 1-3 December 2010 Brisbane, Australia. Brisbane: ACIS, pp. 1 – 10.

Silvola, R., Jaaskelainen, O., Kropsu-Vehkapera, H. and Haapasalo, H., 2011. Managing one master data – challenges and preconditions. *Industrial Management & Data Systems*, 111 (1), pp. 146 – 162.

Spens, K.M. and Kovács, G., 2006. A content analysis of research approaches in logistics research. *International Journal of Physical Distribution & Logistics Management*, 36 (5), pp. 374 – 390.

Spiliotopoulou, G., 2009. Reliability reconsidered: Cronbach's alpha and paediatric assessment in occupational therapy. *Australian Occupational Therapy Journal*, 56 (3), pp. 150 – 155.

Stodder, D., 2011, *Five emerging trends in business intelligence and analytics* [Online]. Available at: http://tdwi.org/issues/2011/08/what-works-volume-32-digital-tabbed-version.aspx [Accessed: 5 January 2013].

Stvilia, B., Gasser, L., Twidale, M.B. and Smith, L.C., 2007. A framework for information quality assessment. *Journal of the American Society for Information Science and Technology*, 58 (12), pp. 1720 – 1733.

Swoyer, S., 2010. *Metadata management: An imperative for your enterprise* [Online]. Available at: http://tdwi.org/Articles/2010/09/22/Metadata-Management-Imperative.aspx?Page=1 [Accessed: 19 December 2012].

Tan, A., 2007, *Asia's business intelligence conundrum* [Online]. Available at: http://www.zdnetasia.com/asia-s-business-intelligence-conundrum-62008617.htm [Accessed: 13 September 2013].

Tapia, R.S., Daneva, M. and van Eck, P., 2007. Validating adequacy and suitability of business-IT alignment criteria in an inter-enterprise maturity model. *Proceedings of the 11th IEEE International Enterprise Distributed Object Computing Conference*, 15-19 October 2007 Annapolis, Maryland. Washington: IEEE Computer Society, pp. 202 – 213.

TDWI, 2008, *TDWI BI benchmark report: Organizational and performance metrics for BI teams* [Online]. Available at: http://mfhammond.com/yahoo_site_admin/assets/docs/TDWI-BIBenchmarkReport.242122912.pdf [Accessed: 19 December 2012].

Teddlie, C. and Yu, F., 2007. Mixed methods sampling: A typology with examples. *Journal of Mixed Methods Research*, 1 (1), pp. 77 – 100.

Thomsen, E., 2002. *OLAP solutions: Building multidimensional information systems*, 2nd ed. New York: John Wiley & Son.

Trauth, E.M. and Jessup, L.M., 2000. Understanding computer-mediated discussions: Positivist and interpretive analyses of group support system use. *MIS Quarterly*, 24 (1), pp. 43 – 79.

Turban, E. and Aronson, J.E., 2001. *Decision support systems and intelligent systems*, 6th ed. Upper Saddle River: Prentice Hall.

Turban, E., Sharda, R. and Delen, D., 2011a. *Decision support and business intelligence Systems*, 9th ed. Boston: Pearson.

Turban, E., Sharda, R., Delen, D. and King, D., 2011b. *Business intelligence: A managerial approach*, 2nd ed. Upper Saddle River: Prentice Hall.

Tvrdíková, M., 2007. Support of decision making by business intelligence tools. *Proceedings of the 6th International Conference on Computer Information Systems and Industrial Management Applications*, 28-30 June 2007 Minneapolis, Minnesota. Washington: IEEE Computer Society, pp. 364 – 368.

UNIRAZAK, 2010. *UNIRAZAK relies on SAS to deliver enhanced performance management for a competitive position in the growing education industry* [Online]. Available at: http://www.sas.com/success/uni razak.html [Accessed: 19 December 2012].

van Teijlingen, E. and Hundley, V., 2002. The importance of pilot studies. *Nursing Standard*, 16 (40), pp. 33 – 36.

Ventana Research, 2010, *Business intelligence and performance management for the 21st century* [Online]. Available at: http://www.ventanaresearch. com/executive_summaries/_espdfs/Ventana_Research_BI_&_Performance_ Management_Benchmark_Research_Executive_Summary_2010.pdf [Accessed: 11 December 2012].

Vitt, E., Luckevich, M. and Misner, S., 2010. *Business intelligence: Making better decisions faster*. Redmond: Microsoft Press.

Vukšića, V.B., Bacha, M.P. and Popovič, A., 2013. Supporting performance management with business process management and business intelligence: A case analysis of integration and orchestration. *International Journal of Information Management*, 33, pp. 613 – 619.

Wahyuni, D., 2012. The research design maze: Understanding oaradigms, cases, methods and methodologies. *Journal of Applied Management Accounting Research*, 10 (1), pp. 69 – 80.

Wailgum, T., 2010, *Biggest barriers to business analytics adoption: People* [Online]. Available at: http://www.cio.com.au/article/367783/biggest_barriers _business_analytics_adoption_people/ [Accessed: 12 November 2012].

Watson, H., Abraham, D. and Chen, D., 2004. Data warehousing ROI: Justifying and assessing a data warehouse. *Business Intelligence Journal*, 9 (2), pp. 6 – 17.

Watson, H.J., Ariyachandara, T. and Matyska, R.J., 2001. Data warehousing stages of growth. *Information Systems Management*, 18 (3), pp. 42 – 50.

Watson, H.J. and Wixom, B.H., 2007. Enterprise agility and mature BI capabilities. *Business Intelligence Journal*, 12 (3), pp. 4 – 6.

Watson, H.J., Wixom, B.H., Hoffer J.A., Anderson-Lehman, R., and Reynolds, A.M., 2006. Real-time business intelligence: Best practices at Continental Airlines. *Information Systems Management*, 23 (1), pp. 7 – 18.

Weber, R., 2004. The rhetoric of positivism versus interpretivism: A personal view. *MIS Quarterly*, 28 (1), pp. iii – xii.

Weerdmeester, R., Pocaterra, C. and Hefke, M., 2003, *Knowledge management maturity model* [Online]. Available at: http://www.providers edge.com/docs/km_articles/KM_Maturity_Model_of_VISION_Project.pdf [Accessed: 12 November 2012].

White, C., 2007, *Using master data in business intelligence* [Online]. Available at: http://fm.sap.com/pdf/mar09/Using%20Master%20Data%20 in%20Business%20Intelligence.pdf [Accessed: 12 November 2012].

Williams, S. and Williams, N., 2007. *The profit impact of business intelligence*, 1st ed. San Fracisco: Morgan Kaufmann.

Wixom, B.H. and Watson, H.J., 2001. An empirical investigation of the factors affecting data warehousing success. *MIS Quarterly*, 25 (1), pp. 17 – 41.

Wixom, B. and Watson, H., 2010. The BI-based organization. *International Journal of Business Intelligence Research*, 1 (1), pp. 13 – 28.

Wixom, B., Watson, H. and Werner, T., 2011. Developing an enterprise business intelligence capability: The Norfolk Southern journey. *MIS Quarterly Executive*, 10 (2), pp. 61 – 71.

Wu, J., 2000, *What is business intelligence* [Online]. Available at: http://www.information-management.com/news/1924-1.html [Accessed: 19 January 2013].

Zikmund, W.G. and Babin, B.J., 2013. *Essentials of marketing research*, 5th ed. Mason: Cengage Learning.

Appendix A

Sample of Questionnaire

Section A: Business Intelligence Implementation

In this section, the questions are divided into four dimensions: Organizational Management, Process, Technology, and Outcome. Please rate your organization’s business intelligence (BI) environment by choosing the option (Initial, Repeatable, Defined, Managed, and Optimizing) that best represents your understanding and perspective.

I. Organizational Management Dimension

1. <u>Vision</u>
   BI vision outlines the direction and desired future state for BI initiatives. Which of the following best describes the BI vision in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- There is no clear vision being defined for BI initiatives. BI is seen as reporting system that tracks regular business activity.	- Individual departments define their own BI vision. BI is seen as analytical system that support analysis tasks and deliver insights.	- A single, strategic BI vision is defined within critical BI initiatives. BI is seen as monitoring system that addresses issues proactively and monitors cross-departmental processes.	- Enterprise-wide BI vision is defined and communicated throughout the entire organization. BI is seen as business-critical system that drives core business processes and optimizes performance against strategic objectives.	- Enterprise-wide BI vision is extended to the entire value chain of organization. BI is seen as a strategic system that allows information exchange between businesses via Web services and provides a competitive edge driving the market.

2. Goals

BI goal is defined in term of objectives which clearly describes tasks to be accomplished or actions to be taken. It is necessary to have a set of specific BI goals to support BI visions and manage BI activities. To what extent do you think BI goals are well-defined and implemented in your organization?

❐ **Initial**	❐ **Repeatable**	❐ **Defined**	❐ **Managed**	❐ **Optimizing**
- The overall BI goal is just to run the business by delivering reports and viewing historical data.	- The overall BI goals are to enable users to perform analysis within each individual department and empower them with insight.	- The overall BI goals are to monitor business activities and increase effectiveness across multiple departments.	- The overall BI goals are to build knowledge, predict business activities, and model results for improving organizational performance.	- The overall BI goals are to provide self-optimizing capabilities to end users and move toward self-service environment.

3. Scope

BI solutions should be extended to all levels of users and support all relevant business processes. Which of the following best describes the BI coverage in your organization?

❐ **Initial**	❐ **Repeatable**	❐ **Defined**	❐ **Managed**	❐ **Optimizing**
- BI is used only by individual users. Only a few of business processes are supported by BI solutions, so silo BI solutions occur.	- BI is used by some departments or business areas. Most of the business processes are supported by BI solutions, but there is still lack of integration between BI solutions.	- BI is used by most or all departments or business areas (within business units). BI program is defined and implemented in which BI solutions are integrated to standardize business processes.	- BI is used across the enterprise (departments and business units within organization). BI solutions are improved to support important business processes.	- BI is used in inter-enterprise level (departments, business units, suppliers, business partners, customers). All relevant business processes are supported by BI solutions.

4. <u>BI awareness</u>
It is vital to develop an awareness of BI capabilities so that organizations will be able to reap full benefits of BI and maximize return on their BI investment. To what extent do you think your organization is aware of BI potentials?

❐ **Initial**	❐ **Repeatable**	❐ **Defined**	❐ **Managed**	❐ **Optimizing**
- There is limited or no awareness of BI potentials for business development.	- Some departments or business areas are aware of BI potentials and recognize BI as a driver for business development.	- Key stakeholders of all business areas are aware of BI potentials and have a defined BI roadmap for business development.	- There is an enterprise-wide awareness of BI potentials and BI is recognized as important in the planning for business improvement initiatives.	- Business stakeholders are able to identify and improve current and future BI solutions to ensure the needs of business users at all levels are met.

5. <u>Strategic alignment</u>
BI strategy is a plan that is intended to attain a particular goal or objective of BI. It is necessary for organizations to have effective BI strategy that is aligned with business strategy and is being updated when necessary. To what extent do you think the BI strategy is properly aligned in your organization?

❐ **Initial**	❐ **Repeatable**	❐ **Defined**	❐ **Managed**	❐ **Optimizing**
- BI initiatives are developed in an ad hoc basis and only aligned with IT strategy. There is no strategic business plan to align BI initiatives with business strategy.	- BI initiatives are developed after business initiatives are in place. But, there is still no strategic plan to align BI initiatives with business strategy.	- Strategic plans for BI initiatives are developed. BI initiatives are aligned with business strategy.	- Enterprise-wide strategic plans support overall business strategy. BI initiatives are coordinated in a common BI program. Alignment model is realized and well-defined.	- All BI initiatives are linked directly to business initiatives. There is continuous modification in alignment model so that BI strategy is adaptable to new business initiatives.

6. Skills and competencies
The level of skills and competencies can affect the performance and ability of an organization to adapt to continuous changes. What is the level of skills and competencies of your organization in delivering BI solutions?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- Skills and competencies for delivery of BI solutions have not been documented and established.	- Basic skills and competencies for data analysis have been established in each BI project but are not documented.	- Most of the necessary skills (e.g., data mining, analytics) and competencies have been documented and applied in running BI projects.	- New, highly-demand skills and competencies are established for upcoming BI projects.	- All necessary skills and competencies are available, documented, and continually improved to deliver high quality BI solutions.

7. Business commitment
It describes the dedication of business management in the adoption of BI. What is the level of commitment from business people in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- There is limited or no business involvement. Business people think that it is not essential to get involved in BI projects as BI is seen as an IT-driven initiative.	- BI is still seen as an IT-driven initiative but the focus of BI starts to shift to business driven. Some business people get involved in BI to guide business activities.	- Some critical BI initiatives are business-driven. Business people drive business requirements and to understand the capabilities and how they can get additional benefits.	- Most of the BI initiatives are business-driven whereby business people are heavily involved in BI initiatives and business roles.	- All BI initiatives are business driven whereby business people are fully involved within BI environment.

8. IT commitment
It describes the dedication of IT management in the adoption of BI. What is the level of commitment from IT people in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- There is minor commitment and support from IT people towards BI projects.	- IT people commit and support individual BI projects only.	- IT people have more defined commitment towards BI development and actively involved in defining BI program.	- IT people have strong commitment towards BI supports and equal roles as business people in defining business strategy.	- IT people are fully committed to BI initiatives whereby they recognize BI as an essential part of the IT strategy.

9. Governance
Governance refers to the authority and control over decision making structure in order to prioritize BI requests and allocate proper BI resources. To what extent do you think the level of BI governance in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- Roles and responsibilities between IT and business stakeholders are unclear. No official authority exists for governance.	- Some ad hoc groups are formed and guided by a department head and a project manager to oversee BI activities, but they lack of necessary authority for governance. Roles and responsibilities between IT and business stakeholders are still not clearly defined.	- Cross-departmental teams are created and guided by a BI program manager. They have authority on some decisions. Business and IT stakeholders play their roles and commit to their responsibilities.	- A steering committee (i.e., representatives from departments and business units) and a working committee (i.e., BI developers and power users such as business analysts) are formed. They have enterprise-wide authority for all decisions.	- Organizational structure for BI governance becomes institutionalized. BI governance evolves and adapts to changing business priorities.

10. Training

Training is needed to ensure all the users have the skills required to perform their tasks and run the business processes. To what extent do you think your organization have a defined BI training plan?

❐ **Initial**	❐ **Repeatable**	❐ **Defined**	❐ **Managed**	❐ **Optimizing**
- There is no formal BI training plan in place for developing skills and competencies.	- Some BI training plans are done in an ad hoc basis and basic BI tool training in the use of BI tools is provided (e.g., run reports, build simple queries).	- BI training plans are well-coordinated and reviewed to improve current skills and competencies. Advanced training in how to use BI tool is provided in the context of the data relevant to each group of BI users.	- Scheduled and ongoing BI training plans are provided to avoid skill gaps and develop new skills to prepare for upcoming projects. End users are trained to handle business processes and keeps up with changes.	- All staffs have grasped high level of skills through comprehensive BI training plans. Evaluation and monitoring training programs are carried out.

11. Sponsorship and funding

Well-justified and detailed budget are needed to carry out BI projects. Which of the following best describes the BI sponsorship and funding in your organization?

❐ **Initial**	❐ **Repeatable**	❐ **Defined**	❐ **Managed**	❐ **Optimizing**
- There is no sponsorship from top management for BI. No specific budget is allocated for BI projects.	- BI projects are sponsored separately by business area management. Departmental budgets are allocated to some ad-hoc BI projects.	- BI projects are mostly sponsored by middle level managers. BI projects are funded by business units.	- BI projects are sponsored by executives who are actively involved in a cross-functional steering committee.	- All BI initiatives are supported by executive management level (e.g., CEO and other C-level executives).

II. Process Dimension

1. Implementation

   Implementation refers to the way how an organization develops and introduces BI into its business environment. Which of the following best describes the BI implementation approach in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- There is no clearly defined BI implementation approach and no planning or formal process in place. All BI modules are carried out across entire organization at the same time.	- There is a formal approach for implementing BI in sequential order, without allowing moving back to previous steps for changes. Several BI modules are carried out across entire organization at the same time.	- Phased approach is used to address changes one phase at a time instead of all changes at once. BI modules are carried out sequentially with different phases (e.g., by module, by department or business unit, or location).	- Incremental delivery approach is used to provide more flexibility in the use of resources. The implementation starts with a prototype system and work in short iteration cycles.	- Agile approach is used to create incremental small releases within a short iteration cycles. The implementation process is iterative, agile, and adaptive to change.

2. <u>Change management</u>

Change management is the process of assisting the organization to manage and coordinate changes to business processes and systems. What is the maturity level of BI change management process in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- There is no formal change management process for BI in place. Change requests are made and solved in an ad-hoc manner. Procedures to manage changes are not well-defined.	- Change management process is defined and applied inconsistently in isolated BI projects. A ticket handling system is used to store and solve requests for change. Many changes are still handled informally without following correct processes.	- A structured change management process is defined and applied across multiple BI projects. Standard procedure is established and documented to approve, verify, prioritize and schedule changes.	- Enterprise-wide BI change management process is defined and applied on every new project or change. Reports about change status including measurements and goals (e.g. response time) are regularly produced.	- BI change management process is continuously improved and fully integrated with continuous business strategy development and other relevant processes. Trend analysis and statistics about change occurrence and success rate are also provided.

3. <u>Master data management (MDM)</u>
MDM is the process of consolidating all master data in different formats and structures into a centralized resource to provide a single, synchronized view of key data entitles. Master data refers to common business data entities (such as customer and product) that are shared by multiple applications across the organization. To which extent do you think a mature MDM program is implemented in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- Master data problems exist but are not identified. Data conflicts, deletions and changes are handled manually.	- Master data problems are identified but action is not taken to resolve the problems. Some data conflicts, deletions and changes are handled automatically.	- A set of defined MDM processes are in place and centralized. Master reference data, business-oriented data rules, and connected processing are centrally handled. Services for integration with master repository are defined.	- Enterprise-wide MDM initiatives are implemented. Service-oriented architecture (SOA) is in place to integrate common business methods and data across applications. MDM processes are monitored and automated to enforce and undo changes to master reference data.	- MDM is fully integrated into business processes and optimized to create a shared vision and strategy. Complete transaction integration are available to internal applications. Data changes are propagated to all application systems that need master data.

4. <u>Metadata management</u>
Metadata refers to data about data, describing where data is being used and stored, the source of data, and what changes have been made to the data. What is the maturity level of metadata management in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- No metadata is available for users to view.	- Metadata is available for users to view periodically through metadata reports that are not integrated.	- Metadata are managed in one or more metadata repository.	- There is a centralized metadata repository that standardizes metadata across different sources for users to access.	- There is a web-based centralized metadata repository for users to access integrated and up-to-date metadata.

5. Data governance

Data governance is a process and structure for managing data as a enterprise assets and enforcing business rules to improve the quality of data. Data stewardship involves managing the ownership and policies. Data ownership refers to the control and responsibility of data. Which of the following best describes the data governance in your organization?

❐ **Initial**	❐ **Repeatable**	❐ **Defined**	❐ **Managed**	❐ **Optimizing**
- There is no data governance approach and stewardship functions. Business data ownership has not been defined.	- A local data governance program is applied, but stewardship activities are not standardized. Strategic ownership has been defined for a few data entities but it is not been formalized and detailed accountability structure is missing.	- Data governance team is set up and stewardship activities are standardized. Ownership and policies have been defined for all major data objects and include strategic as well as operational accountability.	- An executive-level data governance committee is established to oversee data stewardship across the organization. Clear ownership of data has been defined along with formalized escalation paths and mechanisms for data quality monitoring.	- Monitoring and enforcement of data governance are automated. Clear ownership of data has been defined along with formalized escalation paths, mechanisms for monitoring data quality, and mechanisms for continuous improvements.

III. Technology Dimension

1. Data warehousing

   Data warehousing involves creating, maintaining, using, and continuously refreshing data in a repository that is designed for querying, reporting, and analysis. What is the maturity level of data warehousing in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- Spread marts in the form of spreadsheets (e.g., Excel) or desktop databases (e.g., MS Access) are used to support individual needs.	- Multiple independent data marts are used to support departmental or business function needs.	- Multiple data warehouses and data marts are used to support cross-departmental needs.	- An enterprise data warehouse is used to centralize the management of BI resource and make it available as a shared service.	- BI service are embedded within business processes to link enterprise data warehouse and other sources for users to access data in real time through a common interface.

2. Master data architecture

Master data architecture refers to the framework that manages and monitors all the master data available in an organization. Which of the following best describes the master data architecture in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- Master data architecture has not been defined. There is no master data model in place.	- Simple master data architecture has been defined for some master data entities and system landscape, and there is no standardization of architecture between systems. Master data model is created for individual business applications.	- System of Entry and System of Record have been defined for all core master data entities in the organization and there is standardization of architecture for most of the systems. Master data model are defined for specific business functions.	- Robust master data architecture has been defined for all critical master data entities and all systems comply with the architecture. Core master data model exists at enterprise level.	- Master data architecture has been optimized so that it is easily integrated with new systems; legacy applications are being decommissioned or updated to comply with the architecture. Enterprise-level of master data model is continually improved.

3. Metadata architecture
Metadata architecture refers to the framework that manages all the metadata available in an organization. To what extent do you think the metadata architecture is defined and implemented in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- Metadata architecture has not been defined to manage metadata. Business rules are implemented independently in different systems and often directly in the program code or application database.	- Technical and to some extent operational metadata are captured but they are managed separately. Some business rules are isolated in an application layer where they are system parameters.	- Business metadata is being addressed and metadata strategy has been defined for some parts of organization. There are rules for application design that isolates metadata in its own application layer.	- Business metadata is being managed and maintained; Metadata is being actively used and plays important roles in new projects and developments. Applications can source metadata from outside and changes to business rules are managed by business managers.	- Metadata is considered as a strategic resource and the developed metadata strategy includes all applications and tools. Changes of business rules in applications do not require application development but are managed by a business process.

4. ETL (Extract-Transform-Load)

ETL refers to the process of collecting relevant data from different sources, converting data into a consistent format, and loading data into target repository. To what extent do you think the degree to which your organization uses ETL to meet requirements of users?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- There is no ETL capabilities being used within the organization, so necessary data integration tasks are done manually.	- Basic ETL capabilities (often single-system focused) are in place within a department or local environment. There is no standardization of ETL tools across organization.	- Common ETL capabilities that might be cross-system are in place, but not all business areas have adopted these capabilities. Some ETL tools are platform-independence and utilize reusable objects.	- Most of the business areas have used standard ETL tools which utilize reusable objects, templates, standards for integration, multi-server environments, and platform-independence.	- ETL tools fulfill all current and future requirements of the business, and allow easy integration with existing and new systems. All ETL tools have all standard functionalities (e.g., reusable objects and templates for all tasks).

5. <u>OLAP</u>

OLAP is a data manipulation tool that support multi-dimensional data structures and allows users to view and analyse data from different perspectives. To what extent do you think OLAP is implemented in your organization to perform multi-dimensional data analysis?

❐ **Initial**	❐ **Repeatable**	❐ **Defined**	❐ **Managed**	❐ **Optimizing**
- OLAP has not been defined and implemented, so necessary analysis and maintenance tasks are done manually.	- Simple maintenance tasks are automated and basic analysis requirements are fulfilled but there is no integration between data sources for analysis. OLAP solutions are different in term of degree of multi-server environment and degree of automation (e.g., backup).	- Standards for usage and maintenance are documented and integration with several types of data sources is possible. OLAP solutions are standardized by having standard monitoring tools and same degree of multi-server environment and automation.	- Most of the maintenance tasks are automated. Several types of data sources are integrated and standards for implementation are applied. OLAP solutions are platform independent and follow best practices maintenance standards.	- OLAP is scalable and optimized to meet all current and expected future requirements. Standards for integration are applied. OLAP solutions integrate with all relevant systems and offer full automation for all daily maintenance tasks.

6. Reporting and analysis

To what extent do you think the reporting and analysis is used within your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- Users rely heavily on static reports and spreadsheets created by IT to meet specific individual needs.	- Reporting tools become more interactive where ad hoc query and OLAP tools are used to perform data analysis.	- Users are allowed to perform advanced analysis using data visualization techniques (e.g., dashboard, scorecards) to track business performance.	- Interactive and predictive 360-degree view of business need based on individual user is provided. Predictive analytics such as data mining, trend analysis, forecasting, modelling tools and alerts are used.	- Organization moves towards real-time analytics where real time BI applications and rules-based engines are being used.

IV. Outcome Dimension

1. Data quality

   Data quality refers to the characteristic of the data sets to meet the user requirements. Which of the following best describes the data quality in your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- Data are incorrect, incomplete, missing and unreliable. Inconsistencies in data definitions, data formats, and data values.	- Consolidation of different data representations and elimination of duplicate data are done through data profiling and cleansing. However, data cleanup is repeated for every new data set received due to failure to address root cause of data defects.	- Root causes of data quality issues are identified and eliminated through an enterprise-wide data quality assessment. Data are integrated, shared, and reusable for critical business areas.	- Prevention of future data defects from occurring is done through data validation which includes format checks, completeness check, limit checks, and review of the data to identify errors.	- Data quality becomes an integral part of all business processes and data have achieved all aspects of quality dimensions.

2. Information quality

Information quality refers to the characteristics of analyzed or processed data that provide high value to users and meet their requirements. What is the level of information quality in your organization?

❐ **Initial**	❐ **Repeatable**	❐ **Defined**	❐ **Managed**	❐ **Optimizing**
- Information is not ready by time of use and outdated due to information overload. Information is inconsistent, ambiguous, and incomplete. React to information quality problems when occur.	- Information available is locally useful but still cannot be integrated. Same information is produced differently from multiple sources. Information quality issues are addressed, except those issues that are smaller or widespread but not highly visible.	- Information is aggregated, compressed, integrated, accessible, and aligned to organizational information quality requirements. However, the sources of current information quality problems are not investigated.	- Root causes of problems are identified and corrected. The quality of information is continuously assessed and enhanced through processes such as validity assessment, transformation control, and enhancement.	- Information is treated as a product. High quality information is delivered consistently and reliably. Information quality management processes are continually improved.

3. KPIs

Key Performance Indicators (KPIs) are a set of specifically defined metrics tracking outcome that of central importance to an organization. To what extent do you think the use of KPIs identified within your organization?

❒ **Initial**	❒ **Repeatable**	❒ **Defined**	❒ **Managed**	❒ **Optimizing**
- KPIs are financial-based (e.g., revenue growth, return on investment) and developed on an ad-hoc basis, only measure past performance.	- KPIs are function-based and measure future performance, but non-integrated. Financial and non-financial KPIs (e.g., customer satisfaction, product quality) are used.	- KPIs are integrated. Function-based KPIs are supplemented with some process-based KPIs (e.g., percent of perfect customer orders, days to deliver an order).	- KPIs focus on achieving enterprise-wide integration. All KPIs are function-based and process-based (e.g., forecast accuracy, delivery performance, inventory balances, manufacturing cycle time).	- KPIs focus on external and cross-enterprise processes (e.g., supplier performance, new or lost customers) to track the performance of parts of full value chain that lie outside organization boarder.

Section B: Demographic Information

1. What is your primary job title?

   ____

2. How many year(s) of working experience do you have in the business intelligence (BI) field?
   - ❒ Less than 1 year
   - ❒ 1 – 4 years
   - ❒ 5 – 8 years
   - ❒ 9 – 12 years
   - ❒ 13 years and above

3. Which of the following best reflects your organization's industry?
   - ❒ Banking/Financial
   - ❒ Communications/Media
   - ❒ Consulting
   - ❒ Distribution
   - ❒ Education
   - ❒ Energy and utilities
   - ❒ Government
   - ❒ Healthcare
   - ❒ Insurance
   - ❒ Manufacturing
   - ❒ Retail/Wholesale
   - ❒ Others (Please specify: ____)

4. How many employees are there in your organization?
   - ❒ Less than 500
   - ❒ 501 – 1000
   - ❒ 1,001 – 5,000
   - ❒ 5,001 – 10,000
   - ❒ 10,001 – 25,000
   - ❒ 25,000 – 50,000
   - ❒ 50,001 and above
   - ❒ Do not know

5. Which of the followings are your current business intelligence (BI) vendor(s)? (Please select all that are applicable)

	Vendor	Please specify the product name
❐	Actuate	
❐	IBM	
❐	Information Builders	
❐	Microsoft	
❐	MicroStrategy	
❐	Oracle	
❐	QlikTech	
❐	SAP	
❐	SAS	
❐	Others (Please specify)	

6. How long has your department been using business intelligence (BI) tools?
   - ❐ Less than 1 year
   - ❐ 1 – 2 years
   - ❐ 3 – 4 years
   - ❐ 5 – 6 years
   - ❐ 7 – 8 years
   - ❐ 9 – 10 years
   - ❐ 10 years and above

7. Which of the following factors do you think will likely affect the maturity level of business intelligence (BI) tools in your department? (Please select all that apply)
   - ❒ Change management process
   - ❒ Commitment from business
   - ❒ Commitment form IT
   - ❒ Data quality
   - ❒ Skills and competencies
   - ❒ Sponsorship and funding
   - ❒ Technologies and tools
   - ❒ Training
   - ❒ Vision, strategy, goals
   - ❒ Others (Please specify: ____)

Thank you for your time and participation in the survey

Appendix B

Sample of Invitation Letter

Dear Participant,

I am a post-graduate student of Universiti Tunku Abdul Rahman (UTAR), Petaling Jaya Campus, Selangor. Currently, I am undertaking a research study on Business Intelligence (BI) topic. The purpose of this research is to identify and understand the current level of BI maturity in Malaysian organizations.

The survey is divided into 2 sections as follows:
- Section A: Business Intelligence Implementation
- Section B: Demographic Information

The survey will take you about 20 minutes to complete. Your answers are of great value to the completion of this research. All the information provided by you will be kept confidential and only be used for academic purposes. Information identifying the participant will not be disclosed under any circumstances.

Your participation and cooperation would be greatly appreciated. Thank you for sparing your precious time in answering the questionnaire.

Please do not hesitate to contact me at ongil268@1utar.my should you have any doubts or comments on questionnaire.

Thank you.

Best regards,
Ong In Lih

Appendix C

Publication List

Journal:

Ong, I.L., Siew, P.H. and Wong, S.F, 2011. A five-layered business intelligence architecture. *Communications of the IBIMA*, pp. 1 – 11.

Ong, I.L. and Siew, P.H., September 2013. An empirical analysis on business intelligence maturity in Malaysian organizations. *International Journal of Information Systems and Engineering (IJISE)*, 1(1), pp. 1 – 10.

Conference paper:

Ong, I.L. and Siew, P.H., 2013. The impact of organization's demographic factors on business intelligence maturity in Malaysia. *Proceedings of the 3rd International Conference on Research and Innovation in Information Systems – 2013 (ICRIIS'13)*, 27-28 November 2013 Selangor, Malaysia. Selangor, Universiti Tenaga Nasional, pp. 1 – 5. [IEEE Xplore indexed] – The Best Paper Award

Ong, I.L. and Siew, P.H., 2013. Towards the measurement of business intelligence maturity in Malaysian organizations. Proceedings of the International Conference on Business, Accounting, Finance, and Economics (BAFE 2013), 4 October 2013 Perak, Malaysia. Perak: Universiti Tunku Abdul Rahman, pp. 1 – 6.

Ong, I.L. and Siew, P.H., 2013. An empirical analysis on business intelligence maturity in Malaysian organizations. *Proceedings of the International Conference on Emerging Technologies for Information Systems and Business Management*, 11-12 April 2013 Kuala Lumpur, Malaysia. Kuala Lumpur: FTMS College, pp. 285 – 296.

Ong, I.L. and Siew, P.H., 2012. Assessing business intelligence maturity level in Malaysian organizations. *Proceedings of the 3rd International Conference on the Roles of Humanities and Social Sciences in Engineering (ICOHSE 2012)*, 23-25 November 2012 Kuala Lumpur, Malaysia. Kuala Lumpur, pp. 328 – 333.

Ong, I.L. and Siew, P.H., 2012. Four dimensions for business intelligence maturity assessment. *Proceedings of the 2nd Innovation Conference and Exhibition (INNOCONF 2012)*, 17-18 July 2012 Shah Alam, Malaysia. Shah Alam: Politeknik Premier Sultan Salahuddin Abdul Aziz Shah, pp. 92 – 101.

Ong, I.L., Siew, P.H. and Wong, S.F., 2011. Assessing organizational business intelligence maturity. *Proceedings of the 5th International Conference on Information Technology and Multimedia (ICIMμ2011)*, 14-16 November 2011 Selangor, Malaysia. Selangor: Universiti Tenaga Nasional, pp. 1 – 6. [IEEE Xplore indexed]

Ong, I.L., Siew, P.H. and Wong, S.F., 2011. Understanding business intelligence adoption and its values: Some examples from Malaysian companies. *1st Symposium on Information & Computer Sciences (ICS 2011)*, 28 June 2011 Selangor, Malaysia. Selangor: Sunway University, pp. 147 – 150.

Ong, I.L., Siew, P.H. and Wong, S.F, 2011. A framework of business intelligence architecture. *Proceedings of the 16th IBIMA Conference on Innovation and Knowledge Management: A Global Competitive Advantage*, 29-30 June 2011 Kuala Lumpur, Malaysia. Kuala Lumpur: IBIMA Publishing, pp. 1168 – 1176. [ISI indexed]