Utilisation of Data Mining Technology within the Accounting Information System in the Public Sector: A Country Study - Malaysia

by

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Declaration

This work contains no material which has been accepted for the award of any other degree or diploma in any university or other institution, and to the best of my knowledge, this thesis contains no material previously published or written by another person, except where due reference is made in the text of this thesis.

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List of Acronyms and Abbreviations

ICT	Information and Communication Technology
DM	Data Mining
AIS	Accounting Information System
DW	Data Warehousing
ERP	Entreprise Resource Planning
ACL	Auditing Common Language
CAATs	Computer Assisted Audit Tools
KM	Knowledge Management
DMRI	Data Mining Readiness Index
DMR	Data Mining Readiness
TAM	Technology Acceptance Model
DMU	Data Mining Utilisation
DAA	Data Access and Analysis
GFMAS	Government Financial and Management Accounting Systems
BW	Business Warehouse
CIS	Central Information Systems
SQL	Structured Query Language
SAD	Self Accounting Department
TRI	Technology Readiness Index
BAS	Branch Accounting System
e-SPKB	Electronic Budget Planning and Control System
LAN	Local Area Network
HRMIS	Human Resources Management Information System
EG-AG	Electronic Government – Accountant General
GOE	Generic Office Environment
PMS(SETIA)	Project Monitoring System
SPSS	Statistical Package for the Social Sciences
Nvivo7	Qualitative data analysis software
NITA	National Information Technology Agenda
MSC	Multimedia Super Corridor
MAMPU	Malaysian Administrative Modernization and Management Planning Unit
DOD	Department of Defence
GAO	General Accounting Office
NASA	National Aeronautics and Space Administration
FBI	Federal Bureau of Investigation
CIA	Cental Intelligence Agency
JPJ	Road Transport Department
PDRM	Royal Police of Malaysia
PAY	Payroll System
ILS	Investment and Loans System
SLAS	Subsidiary Ledger Accounting System
FMAS	Financial and Management Accounting System
AGO	Accountant General Office
MIS	Management Information Systems
AI	Artificial Intelligence
IT	Information Technology
UTAS	University of Tasmania
ANOVA	Analysis of Variance

Glossary

Accounting Information System (AIS)	An integrated system developed and adopted within department including the accounting systems, payment systems, investment and loans, and financial management.
Data Mining	The process adopted to undertake a thorough analysis of the data, in particular financial data, available to the firm to select the information (identifying patterns and relationships amongst data) to allow the provision of information required by users and, in so doing enhance information available to the decision-making process. A data mining approach will use a variety of technological techniques and tools to explore (summaries, comparison, analysis, forecast, estimate) the data.
Information and Communication Technology (ICT)	Technologies that enable to record, capture, store, process, extract, retrieve, manipulate, transmit, distribute and receive any form of information
Knowledge Management (KM)	Knowledge management is a tool to react to or acquire new knowledge which involves acquisition, storage, dissemination and application.
Data Warehousing (DW)	A data warehouse system is a repository of integrated information, which can be utilized for query or analysis
Data Mining Readiness	The possession by the individual worker of a positive attitude, reflecting both optimism and innovativeness toward adoption or use, strong positive perceptions toward learning new skills and ease of use and to the perceived usefulness of data mining technologies.

Abstract

This study reports on the readiness to implement and the extent of utilisation of data mining technologies within the accounting information systems in the Malaysian public sector. Few studies have investigated the implementation of data mining technology in Malaysia. These studies have been within the private sector. In the public sector there have not been any. This study assists in filling this gap by exploring the role of technology, organizational, human resources and external issues such as political intervention are explored. The characteristics of those who choose too, or would be keen to adopt this technology as compared to non-adopters is also investigated. A data mining utilisation model is constructed combining information and communication technologies (ICTs), knowledge management (KM), data warehousing (DW) and data mining (DM) for application in the Malaysian public sector and the benefits of adopting such a model are considered. The study is triangulated adopting both mail survey and interview techniques. In the mail survey a response rate of 39% was achieved and 9 semi structured interviews were undertaken. Issues explored included the respondents' views of the importance of and factors significant in evaluating the accounting information system, the level of understanding of, perceptions of and readiness to implement data mining technologies within the public sector. Analysis was undertaken using SPSS, and for interview data, Nvivo7.

The results of this study revealed that 25 out of 133 respondents were adopters and had knowledge about the implementation of such technology within their departments. The majority of respondents were not aware of the existence of data mining technology. Results further indicated that while respondents were generally positive about the existing accounting information system they identified improvements and changes that could valuably be made. For both the existing adopters of data mining technologies and non-adopters issues such as technological, organisational and human resources were significant and had played a role in the decision to, or not to utilise such technology. In terms of the non-adopters significant

reasons for not adopting data mining technology included a lack of top management support, constraint on available finance to set up the necessary infrastructure, human resource issues including knowledge of the technology. The study found no difference in gender, job function or utilisation groups in terms of readiness to implement data mining technology but did for the level of education and experience in working with the AIS. The ability to use this type of technology was found to be related to the performance of the AIS. It was found the best model to apply data mining technologies within the public sector would include a centralised data repository linked to a well managed data warehouse integrating a number of existing systems with data mining technology.

Chapter 1

Introduction

1.1 Introduction

Over the years, there has been widespread change in the adoption and utilisation of new technologies in both private and public sectors. Data mining technology is one of the new technologies that have become increasingly popular. It is the process adopted to undertake a thorough analysis of the data, in particular financial data, available to the firm to select the information (identifying patterns and relationships amongst data) to allow the provision of information required by users and, in so doing enhance information available to the decision-making process. A data mining approach will use a variety of technological techniques and tools to explore (summaries, comparison, analysis, forecast, estimate) the data.

This thesis explores its adoption and utilisation within the accounting information system by the public sector in Malaysia. Data mining technology is an important tool for an organisation to use in business today. The government sector is able to use data mining technology in many ways. For example, in audits and investigation of government projects and programs, fraud prevention and detection and also would empower E-Government initiatives. This study investigates the implementation of, the readiness to implement and the utilisation of data mining technology. A Data Mining Utilisation (DMU) research model was explored through the integration of multi-method, a triangulated study. In the development of the research model, related fields such as Information and Communications Technologies (ICT), Data Mining Technologies, Knowledge Management (KM) and also Accounting Information System (AIS) are considered.

1.2 Background

Today technology has allowed the production and storage of vast amounts of information. Added to this information has become a key resource in today's business world and an ability to effectively manipulate this information has become vitally important to management. It is of concern to organisations to identify approaches to critically analyse this information in order to improve decision making. In the business world for example, information obtained from market segmentation, customer profiling, trend forecasting, cross-selling can help decisions makers to learn more about their customers. In the public sector information obtained from similar activities helps to understand client (citizens) needs and identify how to improve delivery systems. Technology provides the key to collating, classifying and manipulating this vast repository of information.

One of the systems which collates and classifies data collected by organisations is the Accounting Information System (AIS). This system provides financial information that can be used to plan, evaluate and diagnose the impact of operating activities and identify the financial position of the organisation. Given that these systems today collect vast amounts of data, this data can be 'intelligently' analysed by data mining technologies - sophisticated and powerful cutting-edge technology that enables the extraction of hidden predictive information from a large database (Kurt, 2004).

This technology is relatively new and requires that awareness of the technology, readiness to implement and skills for its effective usage be developed. Awareness and readiness in accepting this new technology is an important issue. The user of any new technology will act as a primary player in utilising the technology to the best advantage of the firm. The Accounting Information System which provides input for the decision making process would benefit from the features offered by data mining technology. The role of the Accounting Information System has become increasingly important with rapid change in technology which has created new information alternatives that may assist and change the way decisions are made. The Accounting Information System benefits from the use of information technology, therefore, accountants and other stakeholders who relate to the AIS need to be aware of the opportunities arising with technological advances and acknowledge that the technologies will influence their decisions. For example, data mining can play an important role in a decision-making system. It provides a methodology for problem solving, analysis, planning, diagnosis, detection, integration, prevention, learning and innovations (Hedelin & Allwood, 2002, Liao, 2003).

Data mining is capable of answering questions about the past (what has happened), the present (what is happening), and the future (what might happen) (Nemati & Barko, 2002). Data mining and other technology such as data warehousing, database marketing, and Statistical Sales Analysis are a few of ICT tools which give more capacity for the organisation to integrate and access their history or knowledge. Data mining permit analysis and identification of 'hidden' relation in large datasets. By permitting this, the uncovered information previously is now covered and would give more support in the process of decision making.

Carlson (1999) claims that Information and Communication Technology (ICT) can increase productivity, facilitate changes and improve workforce abilities. Data mining is a part of ICT extensively used in many applications within industries particularly in the enhancement of organisational intelligence, decision-making and would contribute towards making the organisation more agile.

1.3 Research problem, objectives and research questions

In Malaysia there has been no literature that has discussed the implementation of data mining technology within the AIS in the public sector. Various studies have shown that new technology has become popular and has been accepted among workers in many environments. This study seeks to address this problem by investigating the knowledge about and readiness with regard to the implementation of data mining technology in the public sector, the impact of its implementation on financial decisions. It is also proposed to develop a model to guide the implementation of data mining in the public sector in Malaysia.

Research Problem:

There is a lack of knowledge of the status of implementation of data mining technology within accounting information system in the public sector in Malaysia, the benefits of implementing such technologies and identification of the best model for implementation in Malaysia.

This has led to the major research question:

To what extent is data mining technology being implemented, what is the level of readiness, what is the perception of its impact and what is the best model to implement such technology in the public sector organisations within Malaysia?

A number of studies have been undertaken to identify the reasons corporations choose to adopt or not adopt data mining techniques and to identify their status in implementing such technologies (Chang *et al*., 2003, Nemati & Barko, 2003, Wah & Abu Bakar, 2003). Literature on data mining adoption in organisations in other countries indicates variables, such as organisational size, culture, attitude of data resource and style of decision making play a role in adoption decisions (Chang *et al.,* 2003). Other variables identified as influencing the decision to adopt include structure, strategy, management systems, human capital, technological factors, competitiveness of outside environment, etc (Spanos *et al.,* 2002, Chang *et al.,* 2003, Wah & Abu Bakar, 2003). In exploring the extent of data mining utilisation within the public sector in Malaysia, identification of attitudes toward current systems, influential factors in the decision to adopt such technology and also reasons for not adopting such technology are important.

To further explore the major research question, a number of objectives have been identified. These objectives will then lead to the research questions that underlie this study:

Objective 1: To explore the level of data mining awareness and readiness within the public sector.

Prior studies of data mining readiness and implementation have been undertaken in the private sector. Evidence suggests that personnel within private sector firms are aware and ready to implement this technology. Studies in the area of telecommunication, banking, and insurance companies indicate that there is a level of optimism and innovativeness among employees indicating the potential to adopt data mining techniques. Readiness can be seen in terms of the adoption of or intent to adopt data mining technologies (Berger, 1999, Chye & Gerry, 2002, Dahlan *et al*., 2002, Chun & Kim, 2004). This first objective of the study is important in contributing to the discussion about the level of awareness and readiness toward technology especially data mining technologies in their everyday working environment. There is no such evidence available to indicate whether or not personnel in the public sector are also aware and ready.

The first research question posed is:

Research Question 1: Do management and staff in the Malaysian public sector have an understanding of the concept of data mining and accept the relevance of the techniques of data mining in day-to-day accounting activities?

Objective 2: To describe how the application of data mining in the Accounting Information System would impact on the decision-making process.

The Accounting Information System (AIS) is the framework consisting of people, and technology that allows for the provision of the financial information required for decision-making (Benford & Hunton, 2000, O'Donnell & David, 2000). The second objective of this study is to describe how the application of data mining within the Accounting Information System impacts on the system's performance and the decision-making process. The adoption of information technology (enterprise resource planning (ERP) systems, data warehouses, electronic commerce, on-line financial reporting within the information system influences the way information system users make decisions (O'Donnell & David, 2000). This issue has not been explored in the public sector in Malaysia.

The second research question posed is:

Research Question 2: In the operation of the accounting information system how would, or does data mining impact on the effectiveness of public sector decision making in Malaysia?

Objective 3: To identify the criteria and the success factors in public sector accounting information systems.

The third objective of this study is to identify the criteria adopted and success factors in public sector accounting information systems in Malaysia. The intention is to identify the role played currently by data mining techniques, and how important these techniques are identified to be. One aim will be to identify whether such technology is crucial in the process of accounting information systems performance's evaluation.

The third research question posed is:

Research Question 3: Is the ability to utilise data mining techniques one of the important criteria in assessing the performance of the Accounting Information System in the Malaysian public sector?

Objective 4: To identify a best practice data mining model for the public sector Accounting Information System (AIS).

The fourth objective is to identify a 'best practice' data mining model for adoption and implementation in the Malaysian public sector Accounting Information System. Understanding the criteria and success factors in the operation of the public sector accounting information system, the role played by the accounting information system in the decision making process, will provide a foundation for the selection of a preferred data mining model to be implemented in the public sector accounting information system in Malaysia and countries at similar levels of development.

The fourth research question posed is:

Research Question 4: What model would allow the Malaysian public sector to best apply data mining techniques to ensure high quality information within the Accounting Information System?

1.4 Justification for this research

In seeking to access to the best information for better decision making the Malaysian government acted to implement E-Government which has also seen significant technological improvements in general within business and increasingly within accounting and audit departments seeking to improve their accounting information system and implement new technologies. The implementation of new technology such as data mining within the accounting environment was expected to be helpful and enhance the quality of information available in decision making. Most of the research on data mining technology focuses on the development, and implementation of various technologies, the process of data mining and its applications on general framework, cross-sales, deviation detection, organisational learning, interface, consumer behaviours, data quality, health care management, prediction of failure, marketing, software integration, knowledge warehouse, and hypermedia (Liao, 2003). It seems that, most of the studies undertaken have been by information system, expert system or databases management researchers. There has been little research which has addressed implementation within auditing, finance and banking. For example, Lampe and Garcia (2004) have brought up discussions on data mining issues which should be considered by the internal auditor in both large and small organisations. Studies describe the use of data mining to forecast the foreign exchange time series process, analysing financial reports, and as an early warning system of economic crisis (Vojinovic *et al.,* 2001, Kloptchenko *et al.,* 2004, Kim *et al.,* 2004).

There have been many studies in the accounting information system that have focused on internal controls, audit, and the relational entity accounting model (Dunn & McCarthy, 1997, Geerts & McCarthy, 1999). Studies on the implication of information technology within the accounting information system have incorporated the decision making process (Benford & Hunton, 2000, O'Donnell & David, 2000). Although there have been a few reports by government organisation such as Government Accountability Office in the United State of America on the utilisation of data mining technology they have not shown how this technology could enhance capability in different environments. However, there are no studies of data mining technology within the Accounting Information System in the public sector in Malaysia. This study seeks to redress this gap in the literature by providing insights into the adoption and implementation of data mining techniques within the accounting information system in the public sector, and to identify an appropriate model for the implementation of data mining in the public sector in Malaysia.

Moreover, the study will assist in the identification of the status of data mining utilisation, public sector staff readiness and awareness of data mining, data mining impact on the Accounting Information System and decision making process. In brief, the results from this research are likely to help Malaysian public sector departments' top management, accountants and ICT personnel obtain a better understanding of the issues of data mining technology within the area of Accounting Information System.

1.5 Research approach and methodology

This study will proceed in the following three stages.

Stage 1: A review of the literature

The literature that addresses data mining including related concepts such as Information, Communication and Technology, Knowledge Management, and also Accounting Information System are reviewed. The review commences seeking to define 'data mining' and identify its application within the accounting information system and the public sector. There has been little work in this area in the Malaysian public sector.

Data mining, specific to the Accounting Information System will be '*the process of collecting, collating and analysing accounting data for presentation in a format allowing the generation of information and the creation of knowledge through the analysis of this information to enhance the decision-making process within the public sector'*.

While the definition of readiness to adopt data mining technology has been defined as '*the possession by the individual worker of a positive attitude, reflecting both optimism and innovativeness toward adoption or use, strong positive perceptions toward learning new skills and ease of use and to the perceived usefulness of data mining technologies'*.

Stage 2: Collecting data from survey and interview

In this study a triangulated approach is to be adopted. Data was collected in two phases. A mail questionnaire was used in the first phase of data collection, respondents were accountants, auditors, and Information Technology personnel within accounting and audit department. Questionnaires were prepared and available in either Malay or English as one approach to enhancing the prospect of a response. The interview schedule was based on the themes developed in the questionnaire. Interviews were conducted in the second phase of the data collection process. These semi-structured interviews were conducted with officers involved with Accounting Information System[1]. Respondents for both the mail survey and interviews were selected from accountants, information managers and auditors.

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[1] Four types of stakeholders of AIS were included, information producers, information custodians, information consumers and data managers (Xu, 2003). They have a common interest into the same data produce by accounting information systems and sometime rely on each other. They can be accountants, information managers or auditors.

It was necessary to gain the approval of the University of Tasmania Ethics Committee and the Economic Planning Unit, Prime Minister Department of Malaysia for both the questionnaire and interview schedule before data collection could commence. Data was collected between February and April 2006.

Stage 3: Data analysis

Once the data was collected analysis was undertaken. In the case of the quantitative data the statistical package adopted was SPSS V.14 software while the package adopted for the qualitative data was $Nvivo_7$.

1.6 Overview of the Dissertation

This study consists of seven chapters, as follows:

Chapter 1 (*Introduction*) provides a general introduction to the dissertation. It conveys the background of the research which leads to aims and problems of this research. In this chapter, the justification for the research and the processes of this research, as well as definitions, are also provided. In addition, the structure and organisation of this dissertation are outlined.

Following the introduction chapter, the second chapter (*Literature Review: Data Mining Utilisation and the Accounting Information System*) presents a literature review on Information, Communication and Technology (ICT), Accounting Information System and data mining. It provides the background of ICT development in Malaysia, potential use of data mining in public sector. This leads to the development of a general definition of data mining, its use within the AIS which is used in development of a research model.

Chapter 3 (*Development of Data Mining Utilisation (DMU) research model*) reviews the literature related such as ICT, Data Mining, and Knowledge Management (KM) in the development of a research model. A research model was developed from a combination of those related disciplines. In addition, ten hypotheses for investigation derived from the model.

Chapter 4 (*Research Design and Methodology*) describes and justifies methodologies in the adoption of the triangulated approach to data collection. The development of instruments, data collection procedure and analysis test adopted in this study is discussed.

Chapter 5 (*Results, Findings and Narrative Analysis*) presents the analysis of both survey and interview data. The analysis is facilitated through the use of SPSS software for quantitative data and $Nvivo_7$ for qualitative data. Demographic profile of the survey respondents and interviewees are presented. Quotations of the interviews are included to reinforce and enrich the research findings from the survey. Interview data also become a major data source for answering final research questions.

Chapter 6 (*Results, Findings and Hypotheses Testing*) presents the result of evaluation of research hypotheses developed in Chapter 3. It analyses the data collected from survey questionnaires using the techniques of comparing means, such as t-test, analysis of variance (ANOVA) and correlation analysis to test and evaluate ten hypotheses.

Chapter 7 *(Conclusions, Limitations and Future Research)* presents the major conclusions of this research. Each research question is answered and discussed. The contributions to the body of knowledge made by this research are outlined. Finally, the limitations of this research are discussed, along with future research recommendations.

1.7 Conclusion

The purpose of this chapter was to lay the foundation for the research by providing background information and introducing the research problem and research questions. Justifications for this research are provided together with the contributions of the research. Then, the research approach and methodology are presented. Finally, an overview of the thesis is discussed.

Chapter 2

Literature Review: Data Mining Utilisation and the Accounting Information System

2.1 Introduction

This chapter presents a review of Information and Communication Technology (ICT) and the importance of the management of data in the Malaysian public sector. In particular, some observations on the utilisation of data mining within the public sector is discussed before focusing on the potential utilisation of such technologies within the Malaysian public sector accounting information system. A utilisation model is developed to facilitate discussion on the application of data mining technologies within the Accounting Information System (AIS) in the Malaysian public sector.

2.2 ICT Background: The Country

Malaysia has a strategic location as a major crossroad linking the East and the West. Malaysia has a diversity of cultures, languages, religions, politics and social beliefs resulting from the influences of, and settlement of early traders and merchants from China, India, Middle East and colonial influences from the Portuguese, Dutch and British. Malaysia is a multiracial and multilingual country. Bahasa Melayu is the official language, but English is widely used in business and government. The other major languages are Mandarin, Chinese dialects, and Tamil (Raman & Yap, 1996).

Historically, the Malaysian economy was based on agriculture and natural resources. The focus has shifted in the 1980s towards an economy which is productivity-driven in terms of industrial development and the utilisation of high technology. Information and Communication Technology (ICT) has become a catalyst for national development for many nations including Malaysia. To enter the globalized world it is necessary for Malaysia to become part of the 'information society' (Raman & Yap, 1996, Goebel & Gruenwald, 1999, Bose & Sugumaran, 1999, Raeside & Walker, 2001) to be able to compete and leverage the benefits of information technology innovation. This is due to the increase in the application of information technology adoption across the world in both the private and public sectors and has resulted in significant changes in facilitating communication and the exchange of information and data to organisations.

2.2.1 Information and Communication Technology (ICT) and its importance for the management of data in the Malaysian Public Sector

In an attempt to facilitate the country's participation in the global environment the Malaysian Government has actively encouraged the development of and application of technology. The Malaysian government took the initiative to establish National Information Technology Agenda (NITA) and the Multimedia Super Corridor (MSC) (Awang, 2004). This is inspired by the belief that ICT would enable organisations to create, manipulate and distribute information and communications more effectively resulting in an improvement in the quality and effectiveness of both private and public sector information access and communication leading to efficient and effective decision making.

The adoption of technology and advances in technology are of interest to all organisations since information technology usage fundamentally alters the domains within which it is implemented (Danziger & Andersen, 2002). Technology may impact at both the individual level such as how a public sector's employee, manager or citizen complete their work and also at the collective level which embraces a group of individual such as workgroups, department, state agencies and ministries (Danziger & Andersen, 2002). In alignment to this view the Malaysian Government has focused attention on the adoption of ICT technologies within its ministries, agencies and departments. In efforts to achieve this, the Malaysian Administrative Modernization and Management Planning Unit (MAMPU)[2] was created. Through MAMPU the Government acknowledges the challenges in planning the implementation of ICT. The challenge for the public sector is to identify and implement the objectives to deliver government services with the aid of ICT to:

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[2] MAMPU is a government agency which responsible to the administrative modernisation and human resources planning for the Malaysian public service. (www.mampu.gov.my).

• Provide an efficient, expeditious, secured and quality service electronically,
• Leverage on ICT and multimedia to enhance productivity in the public sector,
• Facilitate the sharing of resources among government agencies, and
• Be citizen-centric in the delivery of its services.

In an attempt to achieve these objectives the Malaysian government requires that every public sector department works toward a system that provides integration of systems in the generation of information and aspires to support each other while leveraging ICT to achieve these ends. The exploitation of the benefits of ICT is further accelerated under the Electronic Government (E-Government) flagship under which all department and agencies (within Putrajaya) will be linked to create a multimedia network paperless administration. Through these efforts, there will be more integration and sharing of information in soft copies rather than in hard copy paper based communication between agencies.

Data mining technologies are fundamental to the adoption of ICT under E-Government projects as the concept of a common database is one of the considerations in electronic government. For example, the Project Monitoring System (PMS) which was developed to monitor the efficiency and effectiveness of the implementation of government development projects will work in a collaborative environment with workgroup computing, workflow management systems, common database access and messaging services. Data mining technologies play an important role within these databases to satisfy the different kinds of monitoring activities required such as the handling of different types of information and media, information sharing capability among and within the agencies and keeping track record and know-how to facilitate the sophisticated management of project monitoring. Besides the Project Monitoring System, other projects within E-Government initiatives include the Human Resource Management Information

System (HRMIS), General Office Environment (GOE), Electronic Government-Accountant General (EG-AG) and E-Services[3].

All the systems above provide a technological environment for the collection and management of various data. With this data, managerial decisions can then be taken. In the decision making process functions such as statistical trend analysis, forecasting, simulation and data mining are acknowledged to be important. Data mining enables the agencies to classify and synthesize information into various levels with various viewpoints (MAMPU, 1997a, 1997b). In the case of the accounting department, for instance, the use of ICT will result in increased available data being transferred to the audit department for analytical purposes. An accounting system can be seen as a system of accountability, in maintaining, analyzing and contributing to the process of decision making within departments (Llewellyn, 1994). By utilising data mining technologies the productivity of an accounting department in their management of data can be enhanced. The accounting department would be enabled to provide an efficient, speedy, and secure service with better integration and sharing of information between departments.

The good management of financial data via an effective use of data mining technologies would help to ensure that the information flow between departments was good, reliable, and accurate. However, organization theory suggests, management of data, information, knowledge and decision making are constrained by the ability of the decision maker (Nemati & Barko, 2002) to organize and successfully integrate data mining into the organisation. In addition, good internal integration across departments with appropriate technological infrastructures would be expected to improve the speed and quality of government services to the public. However, there is limited knowledge about the level of data mining activity adopted, or technological usage within the accounting system in the public sector. Perhaps this technology itself is very new for public servants and not widely used.

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[3] E-Services includes electronic delivery of driver and vehicle registration, licensing, and summons, utility payments and Ministry of Health on-line information (www.mampu.gov.my)

2.3 Utilisation of Data Mining Technologies within the public sector: some observations

The public sector has an interest in developing the use of data mining technology because of the ability offered by these technologies to perform work related to:

- **Audits and investigation of government's projects and programs.**

Data mining technology would increase confidence by enhancing the process of audits and investigation of government's project and programs. For example, the United States General Accounting Office used data mining to perform audits and investigations work on federal credit card programs, purchase and travel card programs, Department of Defence's (DOD) vendor pay systems, Army military pay systems, Department of Housing and Urban Development housing programs, and Department of Energy national laboratories (GAO, 2003). Data mining was also implemented within the government sector through the demonstration program undertaken by the US Office of Naval Research (Kostoff & Geisler, 1999). They found that data mining (textual) would be of benefit in the integration of their databases, would support strategic decisions and allow the creation of usable databases. Other organisations such as NASA, National Institutes of Health, and intelligence agencies (i.e. FBI, CIA), Department of Defense (Army, Navy, Air Force and Marine Corps) were amongst the adopters of data mining (Carbone, 1998).

- **Fraud prevention and detection**

Data mining technology has the ability to profile common usage scenarios and detect new or different patterns for prevention and further investigations. In the United States, data mining was adopted by Illinois Department of Public Aid to identity health care providers that were billing for services provided in excess of 24 hours in a single day. With this, they are enabled to identify violators and referred the cases into law enforcement agencies.

- **Empowered E-Government initiatives**

Data mining technology also has the ability to turn data into actionable information that government can use to transform the way of interaction with service recipients. It gives the government the ability to proactively make changes upon future needs. A number of key business issues should be taken into account in the consideration of the use of data mining strategies that align with the ultimate government goals in its attempts to launch 'E' projects. These include:

Table 2.1: Data mining uses within e-government initiatives

Issues	Data Mining method	Advantages
Understanding citizen's needs	Citizen profiling	Gain a deeper understanding of citizens' needs and maximize return on program and service investments. Learn who is most and least likely to use a particular service or enrol in a specific program.
Maximizing service delivery	Online service utilisation modeling	Better meet citizen expectations in recommending the mix of services and information that people are most likely to need.
Managing resource allocation	Lifetime cost modeling	Invest in resources wisely – develop programs that minimize the lifetime cost of servicing a citizen. For example, learn who constantly re-enters your system and identify the reasons why they continually re-enter.
Improving citizen relationships	Classification and predictive modeling	Get better results while respecting Web visitors' time and privacy – ask only the questions necessary to improve the relationship.
Developing effective programs	Satisfaction survey modeling	Develop new programs and services based on what people value. Increase satisfaction to ensure program success.
Maximizing program enrollment	Program drop-out modeling	Develop preventative measures to reduce program abandonment by learning why and when participants leave programs.
Preventing online fraud and hacking	Intrusion detection analysis	Ensure your site's security – pinpoint the factors that lead to its vulnerabilities. Identify suspicious patterns that point to an imminent attack and make certain appropriate firewalls are in place.
Designing effective Web sites	Sequence modeling	Improve Web site effectiveness and performance. Discover the major paths through the Web site and determine what content satisfies visitors.

(Source: SPSS White Paper, Making e-government a reality)

Tax agencies have made frequent use of data mining technology in the United Kingdom and Australia to assist in identifying taxpayers evading obligations and to assist in making effective resource allocation decisions (Micci-Barrera & Ramachandran, 2004). Moreover, with the predictive modelling capability offered by data mining tools, tax agencies are more able to identify noncompliant taxpayers in a more efficient and effective manner. It is expected that data mining technology would assist agencies in refining their traditional audit selection strategies to produce more accurate results.

In the case of Malaysia, the Inland Revenue Board would also benefit from data mining tools. The implementation of a self-assessment method (Sistem Taksiran Kendiri) for tax payments identifies an area in which there is a large quantity of data collected and data mining will assist in generating revenue through efficiencies in their operations. As identified in other countries discussed above, efficiencies in collecting tax with minimal problems on noncompliant would definitely increase the benefits for the country as a whole.

Organisations such as Road Transport Department (JPJ), Royal Police of Malaysia (PDRM), Immigration Department, National Registration Department, Health departments, other departments and ministries can also be potential users of data mining application and technology in synthesising their data. For example the Ministry of Health (MoH), is collecting scientific data for analysis to improve the health systems and medication required for the treatment of various diseases. Data mining could be used to assist in making decision about the best treatment to use for different diseases. It can be argued that data mining utilisation would benefit many public sector departments in improving their capability, efficiencies, effectiveness and their delivery services to the general public.

The Accounting Generals Department, Audit Generals Department and Ministry of Finance have various financial data. These departments have the potential to adopt data mining technology to synthesise all financial information that is able to assist in decision making and those of the agencies relying on them. This study will focus on the nature of public sector accounting systems and the potential uses of data mining within that system in Malaysia.

2.4 The Malaysian Public Sector Accounting Information System (AIS) and potential uses of data mining

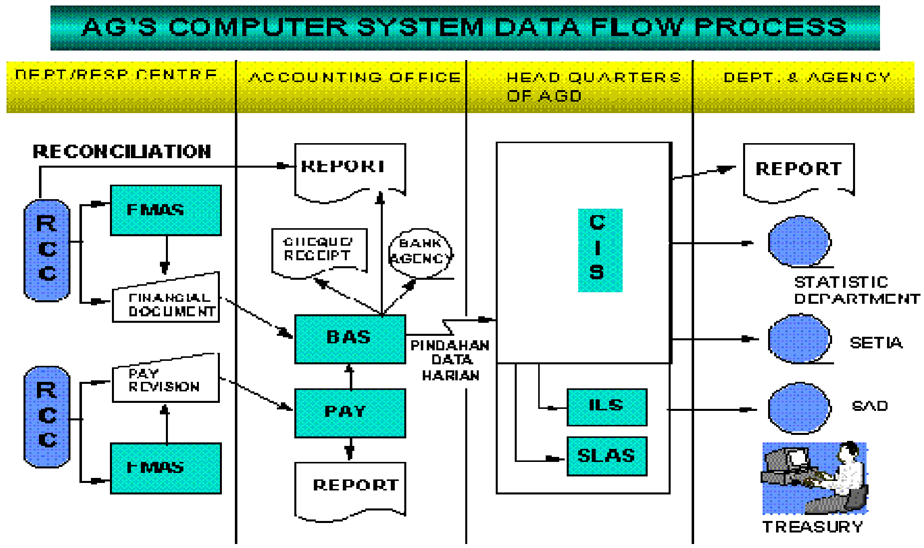
The application of data mining technologies would be of great benefit in assembling the required information for example, in increasing operational efficiencies, fraud detection and enhance the overall decision making in organisations including public sectors (Nemati & Barko, 2002, Lampe & Garcia, 2004).

Accounting and financial systems within public sector agencies are one area in which knowledge based improvements can be made by acting to create both improved and additional financial information, and to improve access to this information. With the use of data mining technologies, it will enhance decision making made by accounting, finance or even the audit department within the public sector of Malaysia.

The Accountant General's Department is the main department responsible to monitor and manage all accounting related data for the public sector. The systems used by the department are shown in figure 2.2 below. They include the Branch Accounting System (BAS), Payroll System (PAY), Central Information System (CIS), Investments and Loans System (ILS), Subsidiary Ledger Accounting System (SLAS) and Financial and Management Accounting System (FMAS).

In Malaysia the data repository focuses on a centralised information system (CIS). The distribution of data (and information) emanates from the Headquarters of the Accountant General's Office (AGO) data warehouse or CIS (see figure 2.2). Data mining technologies, on request for access to data, can then play its role in analysing, interrogating and mining the data for decision making. Data mining has many potential uses in accounting in the public sector: it could assist in dealing with the government's payment to suppliers, government expenditures, for example, on assets and it would increase the department's efficiencies and effectiveness in their operations and enhance their accountability. Data mining use in audits of accounting and financial data could reduce the chance of unethical behaviour and misconduct of civil servants involving bribery and other financial misconduct.

Figure 2.1: Computer system data flow process[4]



The utilisation of data mining to manage, exploit and analyse the data from the centralised data warehouse will increase the performance of reports produced by the department which are then distributed to other departments and agencies, for example to the statistics department, self-accounting department (SAD) and the finance ministry for ministerial decisions. Financial performance could be anticipated with data mining technology (Kloptchenko *et al.,* 2004).

In sum, data mining technologies could be used to analyse the public accounts, and the financial performance of each government department in reaching their objective and controlling their budgets. The technology will increase the ability to access and assess department's financial performance in the management of financial resources. Data mining techniques, neural network for example, have been applied extensively to the task of predicting and forecasting financial variables which assist the assessment of overall systems (Vojinovic *et al.,* 2001, Chun & Kim, 2004). Data mining plays an important role in various fields including financial accounting, management accounting and auditing. Determining profitability, ratios analysis, cost

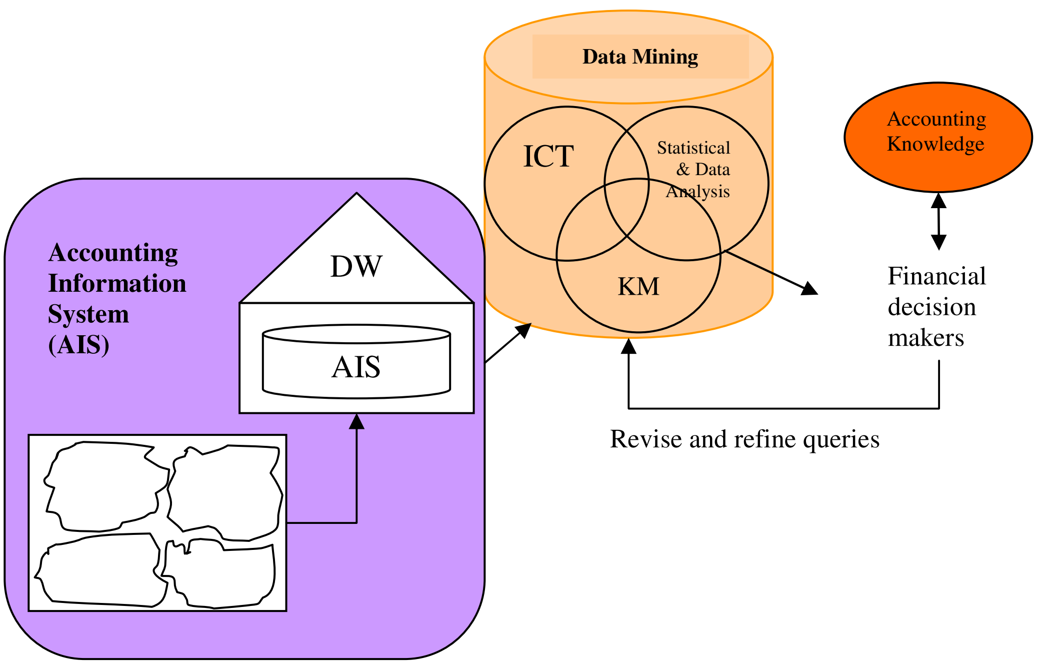
[4] Source: Accountant General Malaysia website (www.anm.gov.my)

analysis and department productivity, analyse management fraud, and examining the effectiveness of the business as a whole. The ability to utilise data mining would be an important criteria which may offer a competitive advantage to users and in the public sector result in better performance in the ability to offer services to the citizens of the country.

2.5 Data mining use within the Accounting Information System (AIS)

In this section a model is developed to identify the use of data mining technology within the accounting information system (see Figure 2.2). The figure illustrates the flow of data from the accounting systems through to the ability to make informed decisions.

Figure 2.2: Data mining use within accounting information systems



The accounting system manages transactions, produces reports and supplies other functions which can integrate with the various systems operating in the agency. This includes the Financial and Management Accounting System (FMAS), Payroll System (PAY) and Branch Accounting System (BAS) which then contributes to the information to Centralised Information Systems (CIS). From this it then integrates with the Investment and Loans System (ILS) and Subsidiary Ledger Accounting System (SLAS).

As proposed by this model, the function of the CIS will act as a master database or data warehouse (DW) which will contain all the data from various accounting systems. Through this, the application of data mining technology which integrates ICT, statistical data analysis tools and knowledge management would enable them to enhance the accounting knowledge for the related decision making process.

2.5.1 What is the Accounting Information System (AIS)?

Over time the Accounting Information System (AIS) has been defined in various ways. It has been seen as a subsystem of the management information systems (MIS) (Uday & Wiggins, 1999). The major function of the accounting information system has been to process financial transactions, as well as non-financial transactions that directly affect the processing of financial transactions. For example, documentation, policies and personnel methods used to prepare accounting reports which support decision making process (Toluyemi, 1999).

Caillouet and Lapeyre (1992) viewed the Accounting Information System as providing financial data for managerial functions such as planning, controlling, providing performance reports of the variances and special reports to analyse problem areas. Similarly, Kaplan *et al.,* (1998) perceived the AIS as retaining and generating the information used by the organisation to plan, evaluate and diagnose the dynamics of operations and financial circumstances. The AIS is a major source of information to decision makers in business organisations and for not-for-profit organisations (Caillouet & Lapeyre, 1992, Uday & Winggins, 1999). Hall (1998) identified four major sub-systems composing the AIS:

• The *transaction processing system*, which supports daily business operations with numerous documents and messages for users throughout the organisation,

• The *general ledger/financial reporting system*, which produces the traditional financial statements, such as income statements, balance sheets, statements of cash flows, tax returns, and other reports required by law,

• The *fixed asset system*, which processes transactions pertaining to the acquisition, maintenance, and disposal of fixed assets, and

• The *management reporting system*, which provides internal management with special purpose financial reports and information needed for decision making, such as budgets, variance reports, and responsibility reports.

In this study, the AIS is taken to mean an integrated system developed and adopted within the Accountant General's Department including the accounting systems, payment systems, investment and loans and financial management. These systems are designed to collect and integrate all data from departmental databases for storage in the centralised data warehouse. This is where all data will be stored and be available to be accessed for further analysis and decision making.

2.5.2 What is Data Mining?

The activity of extracting data obtained from a variety of sources, usually held in a central data warehouse, for evaluation to assist in responding to questions posed, for example, by management. Data mining is a technical term that can be explained in terms of an individual's everyday life experiences, we constantly extract data or information through our experiences and make decisions regarding our activities based on this information In technological terms, the concept of data mining[5] is known as the process of discovering new, valuable information from a large collection of raw data (Fayyad *et al.,* 1996, Brabazon, 1997, Firestone, 1997) and should enable better decision making throughout an organisation (Berry & Linoff, 1997, Nemati & Barko, 2002, Fong *et al.,* 2002, Wen, 2004). Because the architecture of the data mining model integrates various techniques and fields, it has meant different things to different people and it is not surprising that different ways of looking at the concept have taken place.

[5] Other terminology that has been used to find useful patterns in data includes knowledge extraction, information discovery, information harvesting, data archeology, and data pattern processing (Fayyad *et al.,* 1996).

Table 2.2: Data Mining defined throughout the literature

Author	Definition
Fayyad *et al.,* (1996)	Data mining is a step in the knowledge discovery in databases (KDD) process and refers to algorithms that are applied to extract patterns from the data. The extracted information can then be used to form a prediction or classification model, identify trends and associations, refine an existing model, or provide a summary of the database being mined.
Newing (1996)	Data mining is the process of extracting valid, previously unknown and ultimately comprehensible information from large databases and using it to make critical business decisions.
Brabazon (1997)	Data mining is the discovery of new, non-obvious, valuable information from a large collection of raw data.
Firestone (1997)	Data mining is traditional data analysis methodology updated with the most advanced analysis techniques applied to discovering previously unknown patterns.
Berry and Linoff (1997)	Data mining is 'the process of exploration and analysis, by automatic or semiautomatic means, of large quantities of data in order to discover meaningful patterns and rules.'
Fabris (1998)	Data mining is described as the automated analysis of large amounts of data to find patterns and trends that may have otherwise gone undiscovered.
Chung and Gray (1999)	'The objective of data mining is to identify valid, novel, potentially useful, and understandable correlations and patterns in existing data.'
Two Crows Corporation (1999)	Data mining is a process that uses a variety of data analysis tools to discover patterns and relationships in data that may be used to make valid predictions.
Greengard (1999)	Data mining is a group of analytical applications that search for hidden patterns in a database.
McVey (2000)	Data mining is an automated approach for discovering or inferring hidden patterns or knowledge buried in data. 'Hidden' means patterns that are not made apparent through casual observation.
Nemati & Barko (2002)	Data mining is a process that uses statistics, artificial intelligence and machine learning techniques to extract and identify useful information, and subsequent knowledge, from large databases.
Fong *et al.,* (2002)	Data mining is the process of discovering interesting knowledge from large amounts of data that can be used to help companies make better decisions and remain competitive in the marketplace.
Smith (2002)	Data mining is a process that uses a variety of data analysis tools to discover patterns and relationships in data and using them to make valid predictions.
Liao (2003)	Data Mining (DM) is an interdisciplinary field that combines artificial intelligence, computer science, machine learning, database management, data visualization, mathematic algorithms, and statistics. DM is a technology for knowledge discovery in databases (KDD). This technology provides different methodologies for decision making, problem solving, analysis, planning, diagnosis, detection, integration, prevention, learning and innovation.
Wah and Abu Bakar (2003)	Data mining is a variety of techniques such as neural networks, decision trees or standard statistical techniques to identify nuggets of information or decision-making knowledge in bodies of data, and extracting these in such a way that they can be put to use in areas such as decision support, prediction, forecasting, and estimation.
Wen (2004)	Data mining is the process of discovering patterns in data. The process must be automatic or semi-automatic. The patterns discovered must be meaningful in that they lead to an increase in the quality of decision making.
Landry *et al.,* (2004)	Data mining is a variety of tools and processes that can work independently or together to analyse and discover relationships in collections of data.

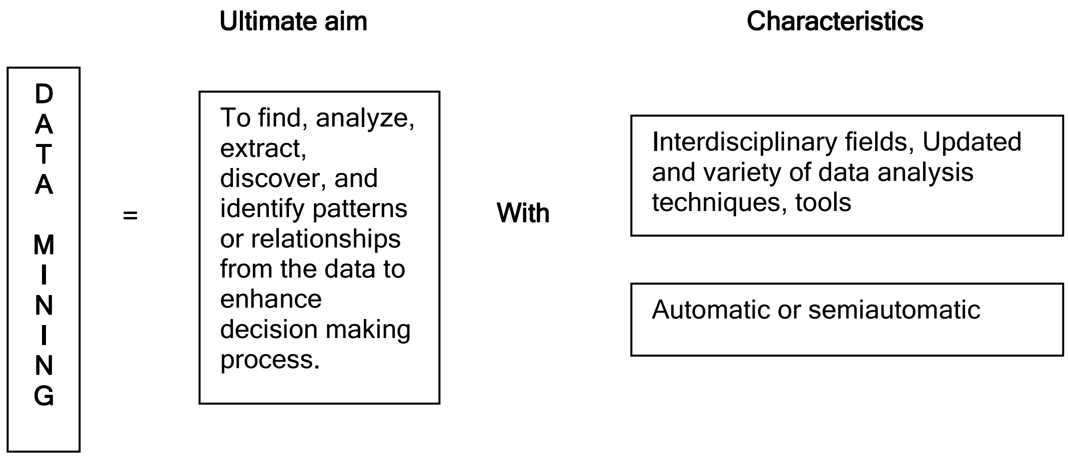
Artificial Intelligence (AI) researchers, statisticians, management researchers, economists might have different ways of looking at this term. Therefore, data mining can be viewed as a combination of ICT, statistical and data analysis, and knowledge management (KM). Consequently, Lampe & Garcia (2004) suggested that there is no universal agreement towards the definition of data mining. The ranges of definitions various researchers have posed are illustrated in Table 2.2 above. In this study the definition used draws together the common elements identified from previous definitions. These elements can be identified as finding, analysing, extraction and identifying patterns or relationships from the data (see, for example, table 2.3 and figure 2.3). In table 2.3 the common elements of the definitions are identified.

Table 2.3: Common elements of data mining definitions

Author	Ultimate aims of the process	Characteristics	
	To find, analyse, extract, discover, and identify patterns or relationships from the data to enhance decision making process.	Interdisciplinary fields, Updated and variety of data analysis techniques, tools	Automatic or semiautomatic
Fayyad *et al.,* (1996)	✓		
Newing (1996)	✓		
Brabazon (1997)	✓		
Firestone (1997)	✓	✓	
Berry and Linoff (1997)	✓		✓
Fabris (1998)	✓		✓
Chung and Gray (1999)	✓		
Two Crows Corp (1999)	✓	✓	
Greengard (1999)	✓	✓	
McVey (2000)	✓	✓	
Nemati and Barko (2002)	✓	✓	✓
Fong *et al.,* (2002)	✓	✓	
Smith (2002)	✓	✓	
Liao (2003)	✓	✓	
Wah and Abu Bakar (2003)	✓	✓	
Wen (2004)	✓	✓	
Landry *et al.,* (2004)	✓	✓	✓

While the difference between definitions can be identified as the way data mining tools are executed, the aims across definitions are consistent. The aim is to provide the means to find, analyse, extract, discover, and identify patterns or relationships from the data to enhance decision making process. Interestingly a number of researchers indicate this assembly of data should embrace interdisciplinary fields and be able to utilise a variety of data analysis tools, and a few indicate that a feature of data mining should automate the process. This is shown in figure 2.3.

Figure 2.3: Data mining definition constructs



In defining data mining, the ultimate aim is to identify the core elements that should be present if data mining is to be effective – these are an ability to find, analyse, extract, discover, and identify patterns or relationships from data. The ultimate goal of data mining is to allow the evaluation of data to provide information that allows a better understanding of what has happened, why it happened and to some extent predict what will happen. This knowledge would assist in the process of making decisions and assist the firm in identifying approaches to increasing competitiveness.

To achieve this ultimate goal, data mining utilise various fields of technologies such as artificial intelligence, neural network, computer science, machine learning, database management, data visualization, mathematic algorithms, and even standard statistical techniques. The combination or integration of these techniques via up to date technologies will be employed to search for useful information through an automatic or semiautomatic process. However, the automation process of data mining was not really an important measurement for those authors in defining data mining as only four out of seventeen definitions reviewed above mention about this issue in their definitions.

For the purpose of this study, a generic definition of data mining will be used:

Data Mining is the process that allows the thorough analysis of the data to draw out the information (including patterns and relationships) that will allow the provision of required information to users and enhance the decision-making process. The data mining approach will use a variety of technological techniques and tools to explore (summaries, comparison, analysis, forecast, estimate) the data.

2.5.3 Data mining in the Accounting Information System (AIS)

Data mining, specific to the accounting information system will be *the process of collecting, collating and analysing accounting data for presentation in a format allowing the generation of information and the creation of knowledge through the analysis of this information to enhance the decision-making process within the public sector organisation.*

Data mining activities (i.e. summaries, comparison, analysis, forecast, and estimate) within the organisation will adopt up-to-date data analysis tools and software which might involve the use of ICT, specific statistical analysis and also the concept of knowledge management (KM) via database management to extract information from large database systems (Thuraisingham, 2000). These three components have substantial influence on the performance of the Accounting Information Systems (AIS) (Hand, 1999, Chopoorian *et al.,* 2001, Hirji, 2001, Spanos *et al.,* 2002, Hedelin & Allwood, 2002, Chang *et al.,* 2003). It is likely that the adoption of these technologies will influence changes in accounting methods, and make the responsibilities of accountants and auditors more challenging. With these technologies, the AIS is able to produce timely, accurate, complete and consistent information as required for decision making purposes. Most of the users of accounting information today require information that is current and continuous (Sutton, 2000). It will include public sector departments and officers who need such information in their decision making process.

Decisions made as a result of information generated by the Accounting Information System rely on the reliability of the presented information and the ability to ascertain that it is reliable. For example, assurance assessments in relation to the content of financial statements. A good financial statement could be produced with the availability of the right data. The need for integrated systems with the capability of producing timely information and the ability to meet reporting deadlines has also put a pressure on the organisation (Carrigan *et al.,* (2003). An appropriate implementation of new technology and upgrading agencies within the core financial management system will improve financial reporting capability, which will not only help managers to make better decisions by obtaining timely information, but will help them meet new accelerated reporting deadlines. ICT infrastructures will provide a platform for the Accounting Information System in terms of collecting, exchanging data, coordinating activities and sharing information (Moxon, 1996, Liao, 2003). This suggests that an accounting database which is able to store large amounts of transaction data is important to decision makers in providing the ability to generate information to assist in choosing the best course of action. This is where the use of statistical and data analysis tools together with a good knowledge of management policies would be useful. This is where data mining would play an important role. Weber (2002) argues that data mining is not only important as a transaction tracing tool in financial auditing but also in offering the ability to undertake overall testing of systems and controls to ensure the firm can produce good financial statements.

The implementation of this tool within the AIS should enable the accounting department to expand the information that can be made available for decision making. The increase in accounting information available through the internet has made data mining important in ensuring users are able to retrieve accounting information with high levels of accuracy and reliability (Debreceny *et al.,* 1999). It also enhances the capabilities of the AIS to play a role in effectively collecting transaction data, providing information for decision makers and assisting in the assurance of internal controls (Burns, 2003).

Stakeholders with an interest in the Accounting Information System within organisations in both private and public sectors, should consider the implementation of data mining in their operations and decision making process. An informed accounting knowledge produced by the Accounting Information System with analysis presented via data mining tools would help in financial decisions. Data mining allows the reiteration of processes allowing for revision and the refinement of queries by users of this information. The Accounting Information System captures a wide variety of transaction data and is used as a primary source of information for an organisation to use in meeting it's goals and objectives. Incorporation of data mining technologies within the Accounting Information System would enhance this process. Mckie (1997) noted that applying data mining software can improve a department's role as a provider for decision makers since the majority of accounting software does not have specific data mining capabilities built-in.

2.6 Conclusion

This review has presented a broad picture of ICT and the accounting information system leading to a discussion of data mining technology within the public sector. The public sector in Malaysia has an opportunity to increase their efficiency and effectiveness by endorsing the implementation of such technology. As in the private sector the public sector accounting information system is a major information provider and the availability of data mining can play an important key role in the decision-making process. It has been argued that data mining could be used to enhance accounting information and improve the capability of the department to make decisions about financial matters. However, there is a limited knowledge about status of data mining activities and its utilisation within accounting information in the Malaysian public organisation. Therefore an exploration of data mining utilisation amongst accounting related departments such as the Accountant General's Department, Auditor General's Department and the Ministry of Finance would offer insights into the adoption and intention to adopt technology and data mining techniques.

Chapter 3

Development of a Data Mining Utilisation (DMU) research model

3.1 Introduction

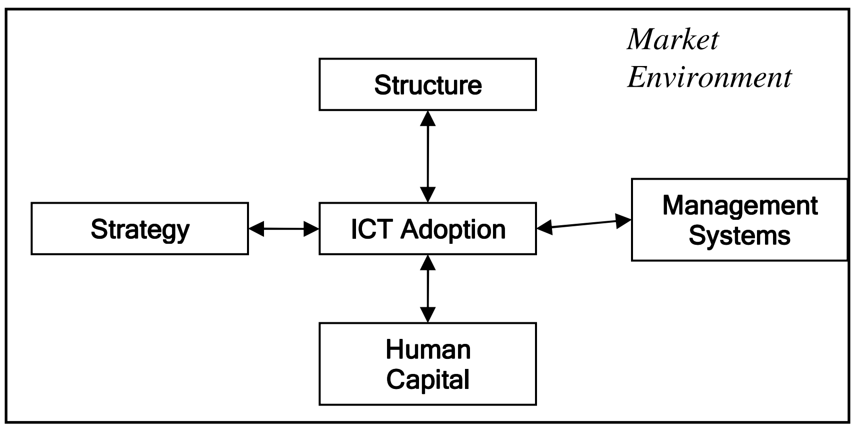
In the development of a research model appropriate to data mining utilisation in the Malaysian public sector previous research in this area are discussed. The literature in the areas of Information and Communication Technologies (ICTs), Knowledge Management (KM), and Data Mining utilisation are discussed together with an examination of the theoretical perspectives in information system research, in particular, the Technology Acceptance Model (TAM) and Data Mining Readiness (DMR). The application of Data Mining utilisation within an AIS model and the following review will establish the foundations for the Data Mining Utilisation (DMU) research model and lead to the development of the hypotheses to explore the current status of usage, the readiness of public sectors managers and staff to the adoption and impacts of data mining technology.

3.2 Influence factor in adopting Information and Communication Technologies (ICTs)

Information and Communication Technologies (ICTs) are now widely accepted as key forces in shaping the economic landscape (Spanos *et al*., 2002), transforming the way we live, learn, work and play (Danziger & Andersen, 2002). ICTs have led to the re-shaping of organisations (Healy & Iles, 2003). ICT is argued to be influential in progressing socioeconomic development, ‘A technological revolution is transforming society in a profound way. If harnessed and directed properly, Information and Communication Technologies have the potential to improve all aspects of our social, economic and cultural life’ (former United Nations-General Kofi Annan, ITU, 2002, cited by Meso *et al.,* 2006, p.186). Many studies have been undertaken to assess the impact of ICTs (Gurbaxani & Whang, 1991, Danziger & Andersen, 2002, Healy & Iles, 2003, Ko, 2003) and to measure the factors influential in the adoption of ICT in various environments such as in health care (Hebert & Benbasat, 1994), in management and business organisations (Chau & Tam, 1997, Spanos *et al*., 2002), in the public sector and within countries (Ang *et al,* 2001, Al-Jalahma, 2003).

Spanos *et al.,* (2002) undertook an extensive study looking at the relationship between ICT adoption and the management perspective toward modernisation and reorganisation. In the study, they adopted and developed Scott Morton's (Morton, 1991) analytical framework which had sought to identify the dynamic relationships involved between ICT adoption and management effort. According to Morton's framework, an organisation is shaped by five forces (technology, strategy, structure, management systems and people). Spanos *et al.,* (2002) used these five forces taking technology (ICT Adoption) as the centre point to study the interrelationship of ICT adoption with the other four forces (see Figure 3.1 adapted from Spanos *et al*., (2002)).

Fig 3.1: Theoretical model - Spanos *et al*. 2002



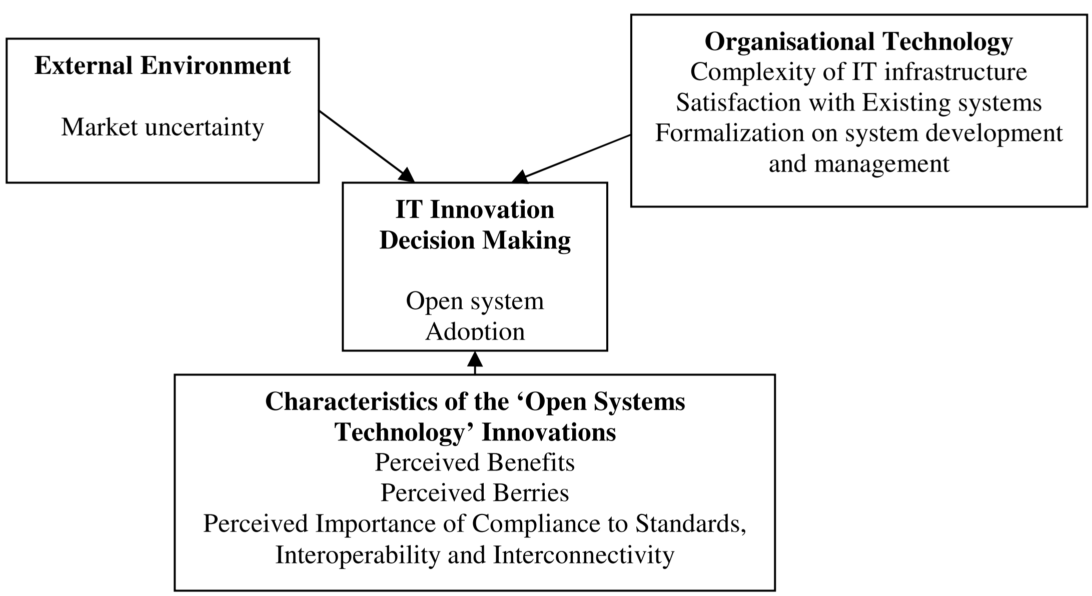
They found that the prospective use of Data Access and Analysis (DAA)[6] was significantly associated with strategic change toward innovation as organisations begin to follow the international trend orientated toward information access and analysis tools. The adoption of ICTs which enhance access to, and extraction of, information was found to be directly linked to securing strategic advantages. This was reflected in the growing belief that the capability of extracting useful information from large amounts of organisational data would result in strategic advantages being gained. A positive association between current and future reduction in hierarchical levels was found, and the use of DAA. This suggests that the adoption of ICTs can

[6] Data Access and Analysis (DAA) technologies, consisting of Data Warehouse that provide easy access to company data, Database Marketing, Data Mining, OLAP, and Statistical Sales Analysis tools. Apart of DAA, Spanos *et al*., (2002) measured ICT adoption with respect to (i) Management Decision Support (MDS) systems, Enterprise Resource Planning (ERP), Technologies for process support and improvement (PSI) and Communication technologies.

promote the effective delegation of operational decision-making and efficiencies in executing tasks. DAA was found to be positively associated with measures used for management systems such as strategic planning, budgeting control and personnel control. The technology is appropriate for extensive data monitoring, analysis, and modelling which provide the basis for systematic exploration and evaluation of alternative courses of strategic action. Human capital especially analytical skills possessed by the employees have been found to be strongly associate with ICT adoption in the organisation (Spanos *et al.,* 2002).

Overall, findings indicate that current and prospective use of Data Access and Analysis (DAA) Technologies are associated with important changes in strategy, organisational structure, management systems and human capital skills. There are two major issues embraced by the framework, that is, *organisational issues* (strategy, structure and management systems) and *human resources issues.* In a study undertaken by Chau and Tam (1997) which explored the factors affecting the decision to adopt an open system of technology, external environment and technological factors (organisational technology and characteristics of that technology) were the focus of the model developed (See figure 3.2, A model for open systems adoption, adapted from Chau & Tam, 1997).

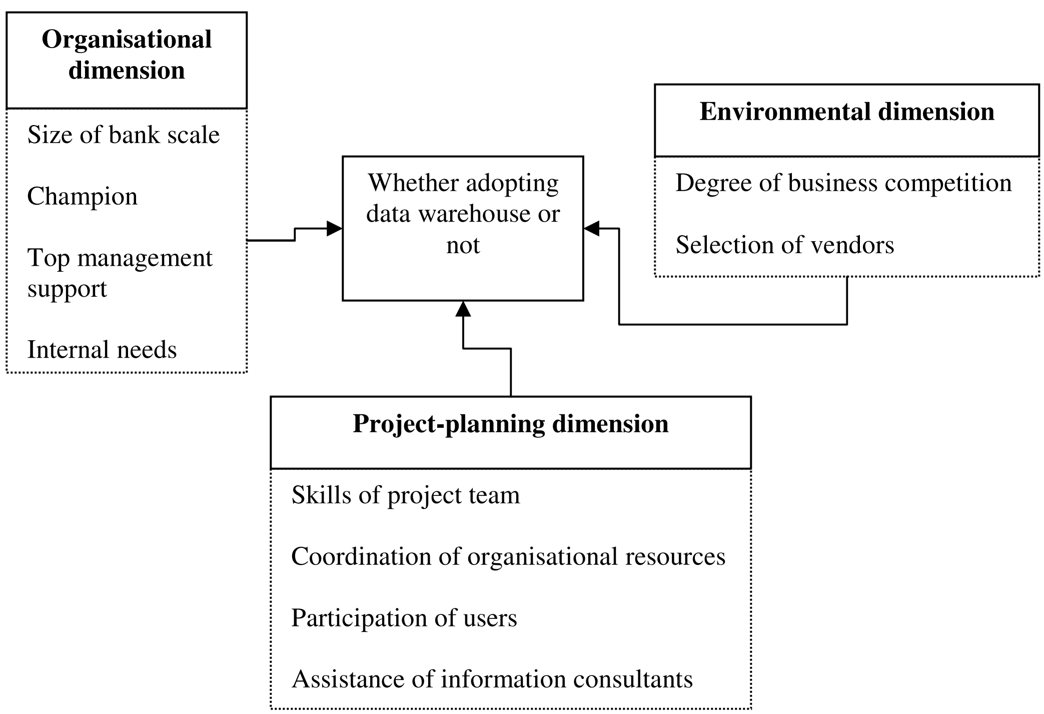
Figure 3.2: A Model for open systems adoption, adapted from Chau and Tam (1997)



Chau and Tam (1997) were concerned about two basic issues, *external issues* (market uncertainty) and *technological issues* (characteristics of such technology, and the organisation of that technology) in their study. This shows that in exploring or investigating technologies adoption, it can be studied from various perspectives. While, Spanos *et al., (*2002) looks at human capital and organisational issues, Chau and Tam (1997) looks at technological and external issues.

Hwang *et al* (2004) looked at the critical factors influencing the adoption of a data warehouse (one of DAA technologies) technology. They considered three dimensions (organisational, environmental and project-planning dimension). This is exemplified in figure 3.3 adapted from Hwang *et al*., (2004). This model reflects external issues (environmental dimension), organisational issues and also human resource issues in the project-planning dimension (i.e. Skills of project team, participation of users).

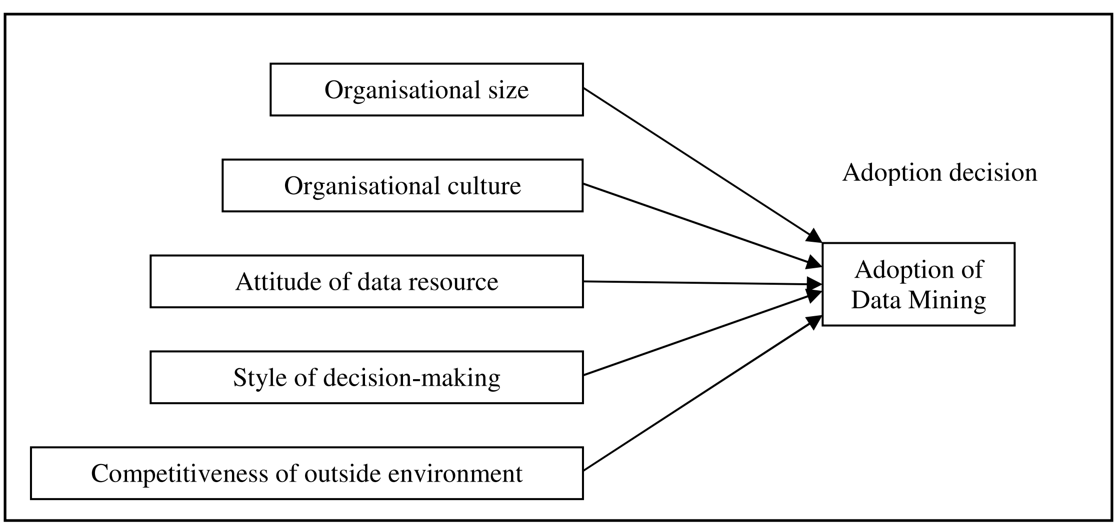
Figure 3.3: Research model adapted from Hwang *et al.,* (2004)



Chang *et al.,* (2003) had a similar dimension in their model, a model in which they specifically addressed data mining techniques. Organisational features considered were size and culture, the attitude of the management of human resources utilising data resources and the style of decision-making and external factors which impact on competitiveness. The features adopted in their study can be viewed in three different dimensions.;that is, organisational, human resources and external.

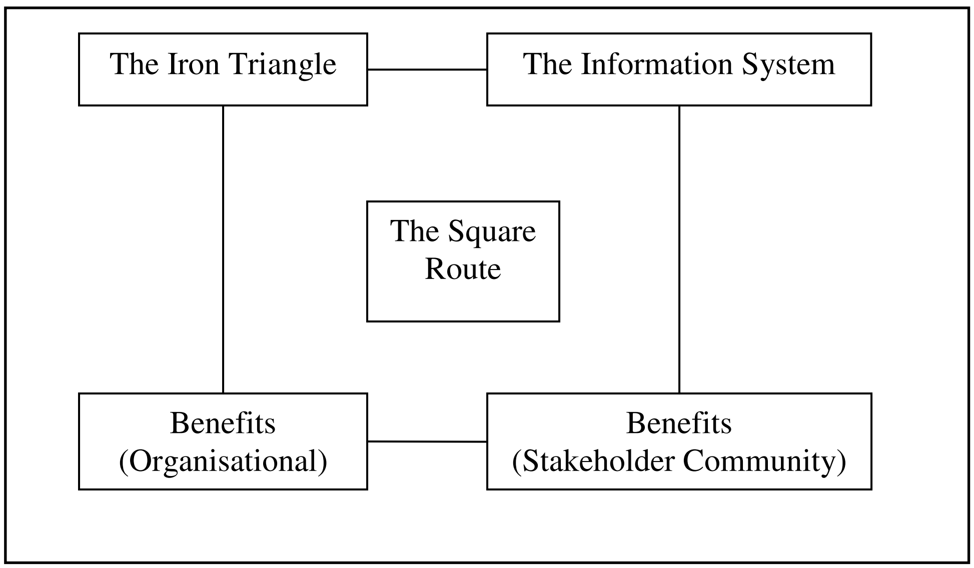
They developed their framework by modifying the research model introduced by Thong and Yap (1995) and Fletcher, *et al.,* (1996) and issues from a series of in-depth interviews of domain managers. In their study they found that the adoption of data mining is significantly related to organisational size, attitude to data resources and the style of decision-making. As data mining is an IT-based application and is costly to implement and maintain the relevance of organisational size is associated with economies of scale in adopting the technology. Data mining was viewed as a data-centered operation and a highly positive attitude toward data reuse by adopters would be expected to influence the decision to adopt the technology. The study also found that participants with less incremental decision making were more likely to adopt data mining. This means that the decision maker tends to make use of the results derived from the data at hand rather than their experiences for decisions (Chang *et al.,* 2003). However, these researchers did not find any statistically significant relationships between two other variables (Organisational culture and competitiveness of outside environment) with the decision to adopt data mining. Their research framework is illustrated in figure 3.4 below.

Figure 3.4: Research framework adapted from Chang *et al.,* 2003



In contrary, Nemati and Barko (2003) suggest that an intense competitive global marketplace (outside environment) has forced enterprise decision makers of all sizes of organisation to develop and deploy data mining technologies to leverage data-resources to enhance their decision-making capabilities. In their study, the Square Route Framework (Figure 3.5) was used. They proposed that this framework empirically describes a number of significant relationships and factors influencing the implementation of data mining technology in the current corporate environment.

Figure 3.5: The square route framework adapted from Nemati and Barko (2003)

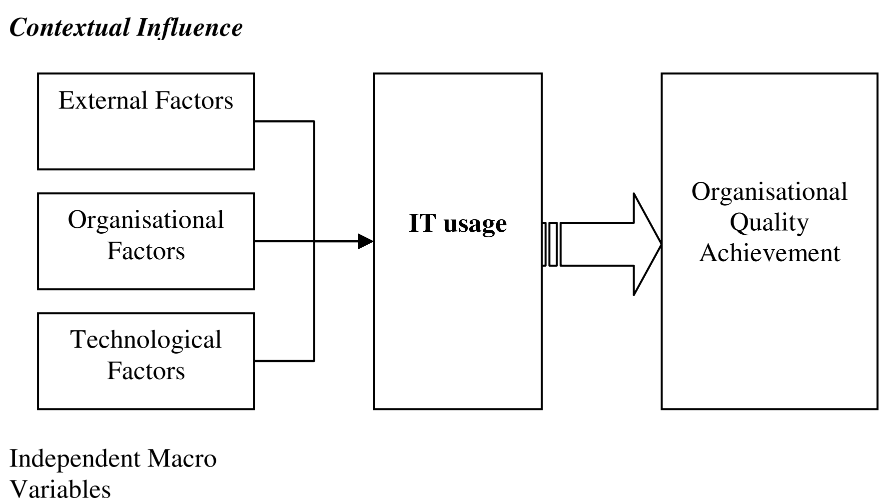


The Iron Triangle (cost, time and quality) were necessary factors in measuring the success of the project (Nemati & Barko, 2003). The framework includes information systems (data and technological), organisational issues, and stakeholders (people).

In the study, information systems *(technological)* issues are based on the notion that data quality, data integration, and technological integration and the level of expertise has play their role in influencing actual project outcomes (Nemati & Barko, 2003). *Organisational* issues includes: clearly defined data mining strategy aligned with corporate strategies, reengineering of business processes to support data mining systems, the presence of new incentive plans to support data mining systems, and the presence of an outsourcing strategy for data mining. In terms of people *(human resource)* issues they hypothesized a positive relationship between the presences of an influential executive, the level of end-user expertise and support from non-IT (end-user, business analyst, etc.) (Nemati & Barko, 2003).

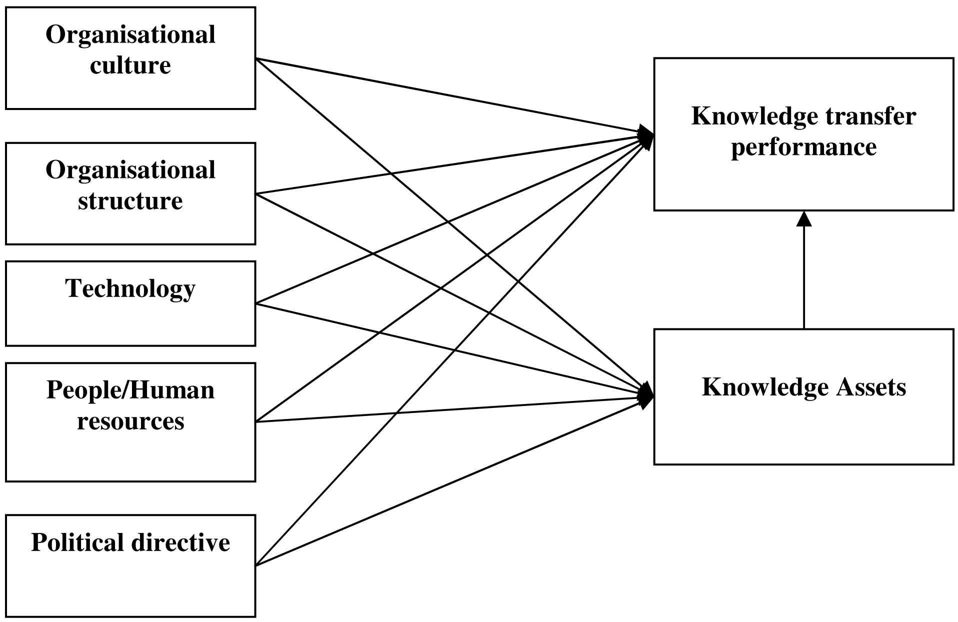
Studies above addressed the business or private sector setting. In the public sector setting Ang *et al.,* (2001) studied factors which influence the ICT usage within the Malaysian public sector and found similarities with the private sector. Three sets of factors were used in their study, *external* (economic climate, IT marketplace, Legislation influence, Public accountability, Inter-organisational, co-operation), *organisational* (structure, size, managerial IT knowledge, top management support, financial resources, goal alignment budgeting method), and *technological factors* (IT experience, IT facilities, user support, IT integration, IT structure, IT competency). Figure 3.6 shows the framework used by Ang *et al.,* (2001). *Human resources* issues however were not separately discussed in this study.

Figure 3.6: Theoretical framework adapted from Ang *et al.,* (2001)



Syed-Ikhsan & Rowland (2004a) considered all four issues in their study of the Malaysian public sector. In their study they categorised five groups of factors to explore knowledge management (KM) status in Malaysian public sector. The five factors that they considered were organisational culture (sharing culture, Individualism), organisational structure (document confidentiality status, communication flow), technology (ICT infrastructure, ICT tools, ICT know-how), people/human resources (posting, training, staff turnover) and political directives (directive from politician) (see figure 3.7). These five factors represent four issues (*organisational, technological, human resources and external issues*) previously discussed. Culture and structure (see figure 3.7) were both directly considering an organisational issues while the other three may represent technological issue, human resources issue and, political directives can represent an external issues.

Figure 3.7: Conceptual framework adapted from Syed-Ikhsan and Rowland (2004a)



The research discussed above indicates the implementation of technology may be influenced by four major issues, that is: a) technological issues, b) organisational issues, c) human resources, and d) external issues. These four issues will be used in developing Data Mining Utilisation (DMU) research model which will be discussed in section 3.5.

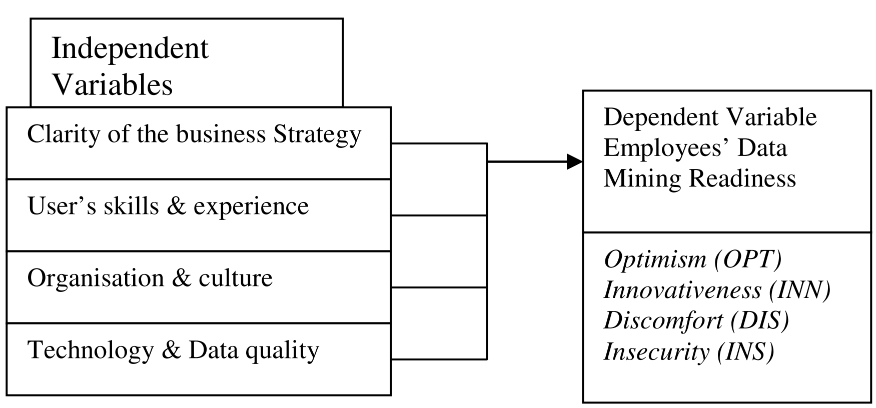
3.3 Data mining readiness

In identifying readiness to adopt data mining techniques a major issue is both the willingness and capability of the work force to accept technology. Human resources primarily on their readiness toward accepting data mining technology can be argued to be the major issue to consider when undertaking or adopting new technology within any organisation (Dahlan *et al.,* 2002, Wah & Abu Bakar, 2002). In this study issues of technology readiness and acceptance by those who actually use and implement such technology will be important. For example, Wah and Abu Bakar (2002) tested end-users (warehouse administrators and decision makers) influence on the implementation of data mining tools. They found that the end-user played an imperative role in the successful implementation of data mining tools. They found issues related to the end-user (lack of knowledge about data mining and lack of required expertise) to be significant factors affecting the decision in adopting data mining.

An exploratory study done by Dahlan *et al.,* (2002) addressed the readiness of employees in adopting data mining technologies. A Data Mining Readiness Index (DMRI) was used to gain a better understanding of the employees' Data Mining Readiness (DMR). Using this index a higher score indicated that the employee was likely to be more effective in a data mining-support role. Contextual variables (organisation, cultural and strategic) that contribute to the employees' DMR were used in their study. In developing the model for their study they incorporated change management issues, the organisation readiness model, technology acceptance model (TAM) and analytical capability model.

Figure 3.8 illustrates the dependent variable (employees' DMR) and the independent variables (business strategy, users' skills and experience, organisational and culture, and technology and data quality) were used in their study.

Figure 3.8: Data mining readiness framework adapted from Dahlan *et al.,* (2002)

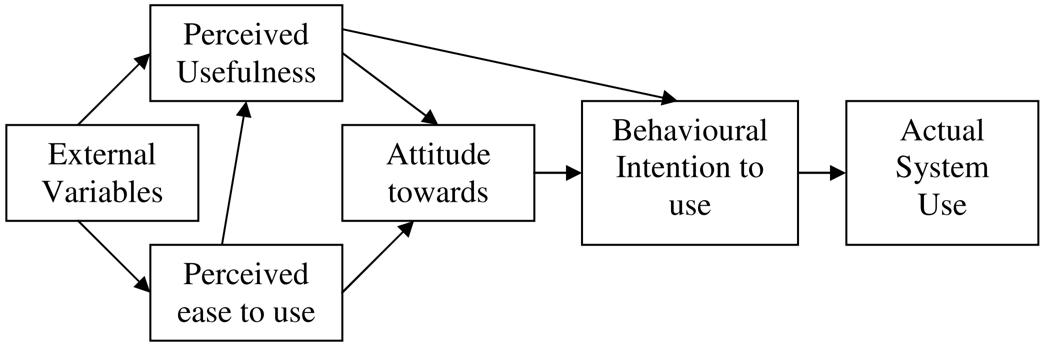


Four dimensions were used in measuring readiness. These were (1) Optimism: A positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives. (2) Innovativeness: A tendency to be a technology pioneer and thought leader. (3) Discomfort: A perceived lack of control over technology and a feeling of being overwhelming by it. (4) Insecurity: Distrust of technology and scepticism about its ability to work properly (Parasuraman, 2000). These four dimensions were divided into two domain feelings or beliefs about technology. Parasuraman (2000) included these in the technology readiness index (TRI) he developed. Technology readiness is defined as 'people's propensity to embrace and use new technology for accomplishing goals in home life and at work' (Parasuraman, 2000, p.308).

The Technology acceptance model (TAM) is a useful theoretical model in understanding and explaining the behaviour towards Information Technology (IT) implementation. Statistically reliable results have revealed the tools to be a good model (Ndubisi & Jantan, 2003, Legris *et al,* 2003) in measuring technology acceptance. Most of the literature on Information Technology adoption focuses on acceptance models which relates to perceptions and beliefs to attitudes, behavioural intention and technology usage (Dahlan *et al.,* 2002, Ndubisi & Jantan, 2003, Legris *et al.,* 2003, Zain *et al.,* 2004).

Two specific behavioural beliefs (perceived usefulness and perceived ease-of-use) are suggested by TAM which reflects on the individual's behavioural intention to use the technology (Legris *et al.,* 2003, Riemenschneider *et al.,* 2003, Amoako-Gyampah & Salam, 2004). Perceived usefulness is defined as the extent to which a potential adopter views and believes a particular technology can offer value over alternative ways of performing the same task. In other word, 'the degree to which a person believes that using a particular system would enhance his or her job performance' (Davis, 1989, p.320) while perceived ease-of-use refers to the degree to which a potential adopter views and expects that the usage of a particular technology will be simple and relatively free of effort.

Figure 3.9: Technology acceptance model adapted from Legris *et al.,* (2003)



New technology utilising data mining techniques is perceived to be useful, easier to use and less complex, has a higher likelihood of acceptance and implementation by potential adopters. Moreover, positive feelings (optimism and innovativeness) increase their readiness to accept the technologies. Positive beliefs and readiness to use technology will encourage employees to adopt technology. In this study, readiness toward accepting data mining will be measured by two readiness drivers (optimism and innovativeness) and two behavioural beliefs (perceived usefulness and perceived ease to use).

Two readiness drivers suggested by the Technology Readiness Index (Parasuraman, 2000) which were used to assess attitude toward computer-based technology, was adopted in the readiness study undertaken by Dahlan *et al.,* (2002) in Malaysia. They found these two drivers were appropriate measures to evaluate level of data mining readiness among respondents. The two perspectives of behavioural beliefs have been adopted in many technological adoption studies (see Legris *et al.,* 2003, Riemenschneider *et al.,* 2003, Amoako-Gyampah & Salam, 2004). Strong perceptions of usefulness and ease of use would be expected to increase the intention to adopt data mining technology for example. A combination of these two readiness drivers and two behavioural beliefs are appropriate to this study. Therefore, readiness to adopt data mining defined as the possession by the individual worker of a positive attitude, reflecting both optimism and innovativeness toward adoption or use, strong positive perceptions toward learning new skills and ease of use and to the perceived usefulness of data mining technologies.

3.4 Individual differences

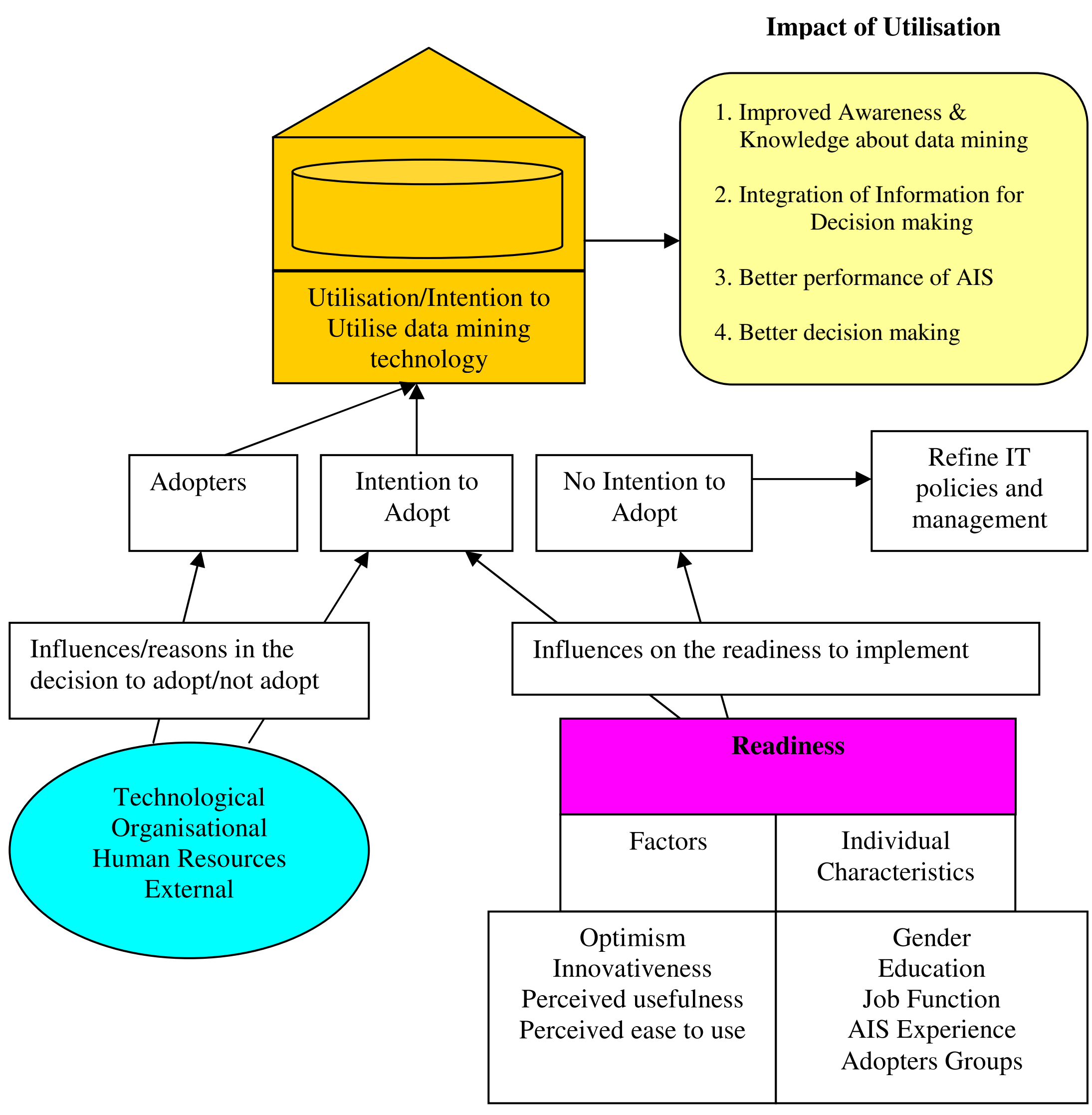
Innovativeness is one of the major components in data mining readiness. Literature on the diffusion of innovation has generalized that individual difference variables such age, education, gender, and position in an organisation are determinants of innovativeness. In information system studies for example, individual differences have been linked to attitudes toward information technology, and the adoption and utilisation of information technology (Agarwal & Prasad, 1999, Venkatesh & Morris, 2000, Kay, 2006). This notion of the crucial role played by individual differences in the implementation of any technology innovation has been a recurrent research theme in a wide variety of disciplines including information systems, production and marketing (Agarwal & Prasad, 1999). Individual differences are one of four general classes of independent variables used in utilisation literature (Trice & Treacy, 1988). Four general classes of independent variables in their survey of the utilisation literature revealed by them were include design and implementation process variables, information system characteristics, individual differences, and task characteristics.

Differences between people affects beliefs, which in turn affect attitudes, intentions and information system utilisation. Gender differences for example have been addressed in studies of computer ability, attitude and use (Venkatesh & Morris, 2000, Kay, 2006). The level of education has been found to have a positive association with beliefs, attitude and readiness toward technology in training environments. In synthesizing prior research, Agarwal and Prasad (1999) found that level of education is negatively related to computer anxiety. It has been argued that higher education enables the development of more sophisticated cognitive structures which lead to a greater ability to learn in new situations. This is because differences in cognitive style might affect one's attitudes (Taylor, 2004). Another characteristic of individual differences is experience. Most studies have found that the proposition stated that experience is positively related to attitude toward technology has been supported (Davis, 1989, Agarwal & Prasad, 1999, Venkatesh & Morris, 2000). Past experiences may have a positive or negative impact on attitude to technology and will influence an individual's belief about the future use/potential of information technology.

3.5 Data Mining Utilisation (DMU) Research Model

In this section the data mining utilisation model to be adopted in this study is discussed. Figure 3.10 depicts a data mining model with utilisation or intention to utilise central in the model. Impacting on utilisation are the factors or reasons identified from previous research that have been found to play a role in utilisation decisions. Readiness to utilise is also built into the model identifying the factors and the influences that have been found to play a role in readiness to implement data mining technology. The final aspect of the model addresses the anticipated impact that the utilisation of data mining techniques will have.

Figure 3.10: Data mining utilisation research model



The four main issues identified as influences/reasons for the utilisation of data mining technologies identified from the literature (technological, organisational, human resources and external factors) were developed as a combination of factors found to influence the adoption of ICT (Chau & Tam, 1997, Ang *et al.,* 2001, Spanos *et al.,* 2002, DAA technologies in organisation (Chang *et al.,* 2003, Nemati & Barko, 2003, Hwang *et al.,* 2004) and knowledge management (KM) technologies in the public sector environment (Syed-Ikhsan & Rowland, 2004a, 2004b). The reasons for not adopting a technology focus more on the first three factors than external issues. Previous literature suggests that reasons such as lack of expertise, lack of top management support were the significant reasons for not adopting data mining technologies (Wah & Abu Bakar, 2002). In this model these issues are important to consider if the Malaysian government is to manage and understand the best approach to implementing data mining tools within the Accounting Information Systems (AIS) in the public sector.

Data mining readiness is embraced in this model. Drivers such as optimism, innovativeness, perceived usefulness and perceived ease of use are addressed along with individual differences that may play a role such as gender, level of education, role within the organisation, years of experience in an AIS function, and whether or not the individual belongs to an adopter group. Optimism and innovativeness were the readiness drivers suggested by Parasuraman (2000) and used by Dahlan *et al.,* (2002) while the two behavioural beliefs (perceived usefulness and perceived ease-to-use) were derived from the technology acceptance model (TAM). Strong readiness will increase the positive attitude toward an intention to use the technology (Davis, 1989, Legris *et al.,* 2003, Riemenschneider *et al.,* 2003, Amoako-Gyampah & Salam, 2004).

It argued in this model that these four variables are the primary determinants of data mining readiness amongst public sector staff and managers. Individual characteristics are expected to play a role in the individual attitude toward information technology, its adoption and reflect on readiness to adopt. Individual characteristics will be used to consider differences between groups (adopters, intention to adopt, and no intention to adopt) and readiness to implement technology. Gender and level of education have been studied in previous work (Venkatesh & Morris, 2000, Kay, 2006, Agarwal & Prasad, 1999) and has been found to impact on attitudes toward technology. Identifying readiness between different individual's job function and experience with technology with regard to their role in the accounting information system, that is, whether they manage documents, keep/enter records, produce statements, prepare budgets, or perform an audit function, may also extend the understanding about readiness among public sector staff and managers. Many studies found that experience is positively related to attitude toward technology (Davis, 1989, Agarwal & Prasad, 1999, Venkatesh & Morris, 2000).

Finally the potential impact of data mining utilisation is considered within the model. In terms of the public sector in Malaysia the impact of adopting data mining technologies is vital. The impact will be felt in improved decision making and performance within the Accounting Information System, additionally growth in the awareness of and knowledge of the benefits of adopting this technology would also be expected. Utilisation and leveraging technology has found to be as an enabler to the improvement of the organisation's performance (Poston & Grabski, 2001). In the business environment for example, it has been shown to improve business performance in client service and client retention (Schlageter, 2005). Accounting firms and related organisations have argued that technological solutions permit result in increased productivity (Schlageter, 2005). The development of technologies will influence changes in accounting methods within the public sector. With the better use of technology, it will enable better performance of the AIS resulting in the production of more timely, accurate, complete and consistent information enhancing the process of decision making. Most users of accounting information require information that is current and continuous in nature (Sutton, 2000). Carrigan *et al.,* (2003) argued that appropriate implementation of new technology and upgrading of core financial management systems would improve financial reporting capability helping managers to make better decisions by obtaining timely information, and enabling them to meet new accelerated reporting deadlines.

The Data Mining Utilisation (DMU) research model developed will identify the relationships between the variables reflecting organisational, technological, human resource and external issues with the adoption and implementation of data mining within the public sector in Malaysia. It explores the level of readiness and its differences in individual characteristics. The impact of data mining toward the performance of AIS and also decision making will be investigated. This model will also assist in exploring the level of awareness and knowledge amongst public servants toward technology itself. The level of awareness and readiness will indicate the intention to use within the department. Any further steps in refining Information Technology policies within the department might be taken from the findings.

3.5.1 Variables in the DMU research model

The variables in the research model have been grouped into the categories identified in the research model developed.

Influential factors and reasons in the utilisation of data mining. Four variables have been identified: (1) Technological (2) Organisational (3) Human resource, and (4) External factors. These four variables were used as they have been found to be influential in many studies on technology adoption and would be likely to play a role in the decision to utilise data mining technologies within the public sector. Specifically looking at reasons for utilisation the factors appear to be internally related rather than reflective of external factors.

Data mining readiness. Individual readiness variables are optimism, innovativeness, perceived usefulness and perceived easy to use. These four variables represent both readiness drivers and beliefs which have been widely used in technology readiness and adoptions.

Impact of utilisation. This will examine the impact of data mining in the AIS and in the decision making process. These variables include awareness and knowledge about data mining, impact on AIS performance and also integration and supporting for better decision making. Awareness and level of knowledge will be used in the model as they provide insights into the awareness and knowledge of data mining within the public sector. The level of awareness and knowledge is expected to have a relationship with readiness and the intention to adopt data mining technology. While variables representing impact of utilisation on the performance of AIS and on decision making process used in measuring the impact of data mining on those two perspectives.

Individual differences. These are represented by demographics variables including gender, education, job function, work experience and a utilisation variable. Utilisation of data mining technologies is measured through a dichotomous measure of use versus non use[7]. These differences will be used to investigate their relation to their readiness toward accepting data mining.

3.6 Research Hypotheses

a) Factors influencing the decision to utilise data mining

Technology is a key enabler in implementing any project, program and strategy due to the fact that ICT is considered as the most effective means of capturing, storing, transforming and disseminating information (Syed-Ikhsan & Rowland, 2004a) and therefore it contributes to the actual outcomes of any organisation's project (Nemati & Barko, 2003). Generally, the facilities that reside within organisations would affect the decision to deploy new technology. Ang *et al.,* (2001) found that an organisation which has comprehensive, centrally co-ordinated technological issues is more inclined to the use of new technology. Other technological concerns such as the adequacy of technical support, compatibility of software with existing operating

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[7] Trice and Treacy (1988) identify three classes of utilisation of information technology measures:

1. The degree of information technology institutionalisation, the measurement by the dependent of user of IT, user feelings of system ownership, and the degree to which IT is routinised into standard operating procedures.
2. A Dichotomous measure of use vs. non-use.
3. Unobstrusive utilisation measure such as connect time and/or frequency of system access.

systems and up-to-date ICT infrastructure would affect the decision to adopt data mining technology.

Spanos *et al.,* (2002) argue that organisational issues such as strategy, structure and management systems were amongst the major forces which shaped the organisation. Organisational attributes such as size, top management support, and internal needs were investigated by Hwang *et al.,* (2004). In their study, they (Hwang *et al.,* 2004) found those organisational factors such as size, an existence of champions (individual who often appreciate the adoption of new technology in an organisation and usually stimulate their associates and staff to support their ideas), top management support and the internal needs of an organisation were the key factor affecting adoption of new information technology.

People are another important element that must be considered in the employment of new technology such as data mining. This is in line with the notion that technology projects depend on the support of people for success, in particular those people who are knowledgeable and experts in the use the technology to be introduced. Spanos *et al.,* (2002) studied human resources forces and found that, employee's analytical skills are strongly associated with information technology use of DAA technologies. The finding indicates that organisation with personnel who possess required analytical skills will be capable of understanding and utilising the new technology. A positive association was also found between the prospective use of DAA technologies and an increased emphasis on leadership skills. Chang *et al*., (2003) found that human resource issues such as attitude of employees toward data resources is significantly related to the adoption of data mining technology.

Ang *et al.,* (2001), identified external issues as a set of factors which influenced technology usage in the public sector setting. This study considered political directives, public accountability, and changes in the private sector environment. Political influences for example can have significant impacts on the decision making process in the public sector. Sometimes there are unwritten policies or directions that need to be followed by the public organisations (Syed-Ikhsan & Rowland, 2004a). In their study, Syed-Ikhsan and Rowland (2004a) found that there was a positive relationship between external issues (political directives) and the creation of knowledge assets through knowledge management technology initiatives. Ang *et al*., (2001) found public accountability (an external issue) to be significantly related to the use of information technology. The public sector would appear to recognise technology usage as a tool to assist in meeting their public accountability. This is because public sector organisations are accountable for the money entrusted to them, and for the outcomes of departmental projects (Hyndman & Anderson, 1991).

In the present study these four issues, namely technology, organisational, human resources and external issues are adopted in identifying the important factors which influence the decision to utilise data mining within a public sector. It is hypothesised:

H1: Technological, Organisational, Human Resource and External issues are significant influences in the decision to utilise data mining technology.

b) Reasons for not utilise data mining

The characteristics of technology itself can sometimes be a deterrent in the decision to adopt or utilise new technology. Technical aspect such as complexity, time required, and difficulties in selecting appropriate software packages has been cited as a reasons for not adopting new technology (Chung *et al.,* 1997). For instance, complexity of infrastructure has to be mediated and matched with the characteristic of the current technological setting of organisation (Chau & Tam, 1997). In their study they also suggest that satisfaction with current systems and technology is likely to lower the incentive to change or to move to a new technology.

Organisational issues such as top management commitment has been found to be important and a necessary condition to move the organisation forward in a particular direction, along with technical thinking, experience and planning (Keen, 1993). As a result top management support has been a key factor affecting the adoption of a new information technology (Zmud, 1984, Scott & Bruce, 1994, Hwang *et al.,* 2004).

This support signals that the changes are important and will be supported. Often this also means that financial support and other resources will be made available to ensure the project is progressed (Dahlan *et al.,* 2002, Chang *et al.,* 2003, Hwang *et al.,* 2004). Calderon (2003) found reasons for not utilising data mining to be a result of resource constraints including lack of funds and lack of top management support.

One of the major issues in adopting data mining technology is the workforce - they are the end-user who exploits technology at the operational level. This is the people factor, staff must have the necessary skills or be trained to use the technology, be aware of the need for this technology, and have developed a supportive attitude toward technological change. Where these requirements are not present progress toward the utilisation of new technology is likely to be impeded (Spanos *et al.,* 2002, Nemati & Barko, 2003, Syed-Ikhsan & Rowland, 2004a, 2004b).

For the purpose of this study three major issues are to be addressed to identify the reasons for the adoption or impediments to the adoption of and the utilisation of data mining technology within the public sector – they are, technology, organisational, and human resources reasons. It is hypothesised that:

H2: Technological, organisational and human resource issues are significant reasons in the decision not to utilise data mining.

c) Knowledge about and intention to utilise data mining

In terms of knowledge, awareness and the intention to utilise data mining technology, this would be argued to be a point at which a potential adopter learns about the existence of the capability of the technology and gains some understanding of the way this technology could function in assisting the firm achieve it's goals (Cooper & Zmud, 1990). The intention to adopt would be a positive response from management that a particularly technology will be implemented for example, a specific data mining technique and the associated software package. The intention to use technology is influenced by two specific behavioural beliefs from the technology acceptance model (TAM). These two beliefs are perceived usefulness and perceived ease of use (Legris *et al.,* 2003, Riemenschneider *et al.,* 2003, Amoako-Gyampah & Salam, 2004). An awareness of data mining terms and also knowledge of data mining will contribute to the intention to utilise technology. Specifically, the research model developed will investigate the relationship between knowledge of data mining and the intention to utilise technology.

H3: There is a significant relationship between knowledge of data mining and the intention to utilise data mining tools.

d) Individual differences in data mining readiness

Individual differences such as age, gender, education, job function are argued to influence innovativeness which then contributes to the readiness to implement technology (Trice & Treacy, 1988, Agarwal & Prasad, 1999, Venkatesh & Morris, 2000, Taylor, 2004, Kay, 2006). Individual differences relating to user characteristics have been incorporated into information systems research for more than 30 years (Taylor, 2004). Cognitive style was one of the perspectives of individual differences which was found to affect information system design and use. An understanding of these individual characteristics and differences are likely to enhance the understanding of the general readiness of employees within the public sector to adopt data mining technology. Individual difference also affect the way people acquire values, form attitudes and elect behavioural intentions (Gefen & Ridings, 2003).

Of the few studies, there is some evidence that the attention has been given to the gender effects on technological perception and outcomes. For example, a number of studies undertaken have found mixed results regarding attitude toward and development of technological skills (Venkatesh & Morris, 2000, Kay, 2006). Although in Malaysia, there is a policy of equal opportunity for both males and females to participate in government and to hold positions in government departments, in terms of technological acceptance however it is suggested that there is a difference between genders in the Malaysian public sector toward data mining. It is hypothesised that:

H4: There is a significant gender difference in the readiness to adopt data mining technology.

Ventakesh & Morris (2000) argue that the level of education results in a difference in the acceptance of technology. It is argued that a higher level of education and training in the workplace will create greater readiness toward the adoption of data mining technology. The level of education has been found to be negatively related to computer anxiety (Igbaria & Parsuraman, 1989). The level of education is suggested to be indicative of a potential adopter's ability to learn and therefore, should be positively associated with beliefs and perceptions. In respect of cognitive style, greater ability to learn and shaping the perception perhaps acquired through higher education (Agarwal & Prasad, 1999). The following hypothesis is posed:

H5: There is a significant difference between different levels of education in their readiness toward data mining technology.

Job function and job level are found to correlate with cognitive style (Taylor, 2004). Cognitive style associates with the thinking processes possessed by an individual (Riding & Saddler-Smith, 1997) and is concerned with how they solve problems, relate to others and learn (Taylor, 2004). Several studies have found differences in cognitive style between different job functions even in the same organisation (Allinson & Hayes, 1996). They found that personnel managers are more intuitive than production, marketing and financial managers suggesting that accountants and bank managers are highly analytical. The implication of these findings suggests that similar or the same job function will require individuals to possess similar cognitive styles.

In this study job function will be tied to involvement in the accounting information system (AIS). Although it is suggested that accountants, auditors and information system personnel require similar and highly analytical cognitive styles, the differences in actual function of these group may also result in differences in cognitive style. It is hypothesised that:

H6: There is a significant difference between the different job functions of respondents and their readiness toward adopting data mining technology.

A number of researchers have argued that years of experience in various job roles are positively related to the attitude they have to the adoption of technology (Davis, 1989, Agarwal & Prasad, 1999, Ventakesh & Morris, 2000). As Agarwal and Prasad (1999) suggests that those who have greater prior experiences with similar technologies are likely to have more positive beliefs about new technology. This supports the notion that as direct experience with technology increases over time, individuals will have a better assessment of the benefits and costs associated with using that technology (Ventakesh & Morris, 2000). In this study, it proposed that the longer the individual has been in the department and involved with the Accounting Information Systems (AIS) the more likely they are to have a positive attitude toward the acceptance of data mining technology. The proposition made is based on the notion that involvement within the Accounting Information System will directly involve individual with computer technology in the work place. It is hypothesised that:

H7: There is a significant difference between experience in involvement in the AIS (number of years) and the readiness to implement data mining.

Utilisation groups are classified into one of three groups - adopters, non-adopters and 'don't know/not aware' - dependent upon their response. It is believed that there will be different level of readiness between these three different groups. Having no knowledge about such technology would impact on the readiness to accept that technology as they would not adopt the technology since they were not aware of it. While groups which have knowledge would be expected to be have a higher readiness toward it but have made an informed decision whether or not to adopt it. To explore the level of readiness among these groups it is hypothesised that:

H8: There is a significant difference between adopter, non-adopter and do not know (not aware) groups in their readiness towards data mining technology.

e) Impact of data mining (AIS performance, Decision Making) and knowledge

The adoption of information technology and information systems may influence the way information system users make decisions (O'Donnell & David, 2000). The utilisation of data mining tools will influence change in practices and impact on the decision making process. An implementation of such technology for example in audits has become more crucial in detecting fraud (Harding, 2006).

The perception of the impact of data mining technology adoption can be examined by considering two perspectives – performance of the AIS and the decision making process. Gurbaxani and Whang (1991) studied the impact of information technology on the organisation and the firm's market. They found that adoption of information technology has enabled organisations to process decision-relevant information in more cost effective way. It was also improving the quality and speed of manager's decision making processes. The utilisation of information systems and technology was also found to be effective in reducing internal coordination cost[8].

For this study, the potential impact of data mining utilisation will focus on the performance of the accounting information system itself and the decision making process within public sector department. Although not the sole source of information, accounting information is important in the decision making process. By implementing new information technology decision support it would be argued that, more meaningful information can be generated by the accounting information system.

[8] Reduction of internal coordination costs, has advantages for firms enabling them to grow horizontally and vertically. Megafirms, such as IBM have capitalised on information technology to obtain such reductions, while also achieving scale economies in operations and reducing market transaction costs (Gurbaxani & Whang, 1991).

The systems maintain and produce the data used by organisations to plan, evaluate, and diagnose the dynamics of operations and financial circumstances (Kaplan, *et. al*., 1998). Therefore, the performance of the AIS will directly affect the holistic performance of the entity including the decision making process. ICT, decision support systems (DSS) and executive support systems (ESS) are increasingly being used in organisations to support managerial decision making. Those systems enhance decision making by allowing managers to select, format, and display information and analytical results in more usable formats (Carey & Kacmar, 2003). Data mining tools could play a role in supporting decision makers. The utilisation of data mining tools within the accounting information system (AIS) can assist in supporting the production of reliable information and assist in creating new information alternatives that may change the way decisions are made, for example the presentation features and access to a databases (O'Donnell & David, 2000). It is hypothesised that difference levels of knowledge about data mining techniques will affect the perception the individual has of the impact of data mining. It is argued that the greater the knowledge of data mining techniques the greater the expectation of the potential impact that data mining might have on performance of the Accounting Information System and within the decision making process.

H9.1: Respondents with a greater knowledge of data mining technology have a higher perception or expectation of the impact of data mining on the AIS than those with less

H9.2: Respondents with a greater knowledge of data mining technology have a higher perception or expectation of the impact of data mining on decision making process than those with less

There are various surrogate measures of performance which have been used in previous studies which can be divided into four major categories. That is, user satisfaction, system use, decisional performance and organisational performance (Choe, 1996, 2004). In this study, AIS user satisfaction and its assessment in terms of data quality the system can produce will be considered a surrogate measures for the performance of AIS. Quality components will include accuracy, up-to-dateness, completeness and consistency of the data. It is expected that the ability of public sector department to utilise data mining technology would have a relationship with the performance of AIS. It is hypothesised that:

H10: There is a relationship between the ability to utilise data mining and the performance of Accounting Information System.

3.7 Conclusion

The research model was developed in this chapter after considering earlier studies. The research variables and their associated relationships were identified and articulated. This model will form the basis for the investigation of the utilisation of data mining within accounting information systems in public sector organisation in Malaysia.

Chapter 4

Research Design and Methodology

4.1 Introduction

In this chapter the research design and methodology to be adopted will be discussed in the development of a triangulated research methodology to be adopted. A survey questionnaire will be administered followed by a number of semi-structured interviews to enrich the data collected.

4.2 Research Design

The research design is addressed within this chapter. As suggested by Cooper and Schindler (2003), the essentials of the research design will include:

- The design is an activity and time-based plan
- The design is always based on the research question
- The design guides the selection of sources and types of information
- The design is a framework for specifying the relationships among the study variables
- The design outlines procedures for every research activity.

It is the research design that will form the basis for the conduct of the current study, and reflect the blueprint or plan for the collection, measurement and analysis of data collected in this study.

The main research question addressed in the present study addresses is: *'to what extent is data mining technology being implemented, what is the level of readiness, what is the perception of its impact and what is the best model to implement such technology in the public sector organisations within Malaysia'*. This question is then refined into four more specific research questions:

1: Do management and staff in the Malaysian public sector have an understanding of the concept of data mining and accept the relevance of the techniques of data mining in day-to-day accounting activities?

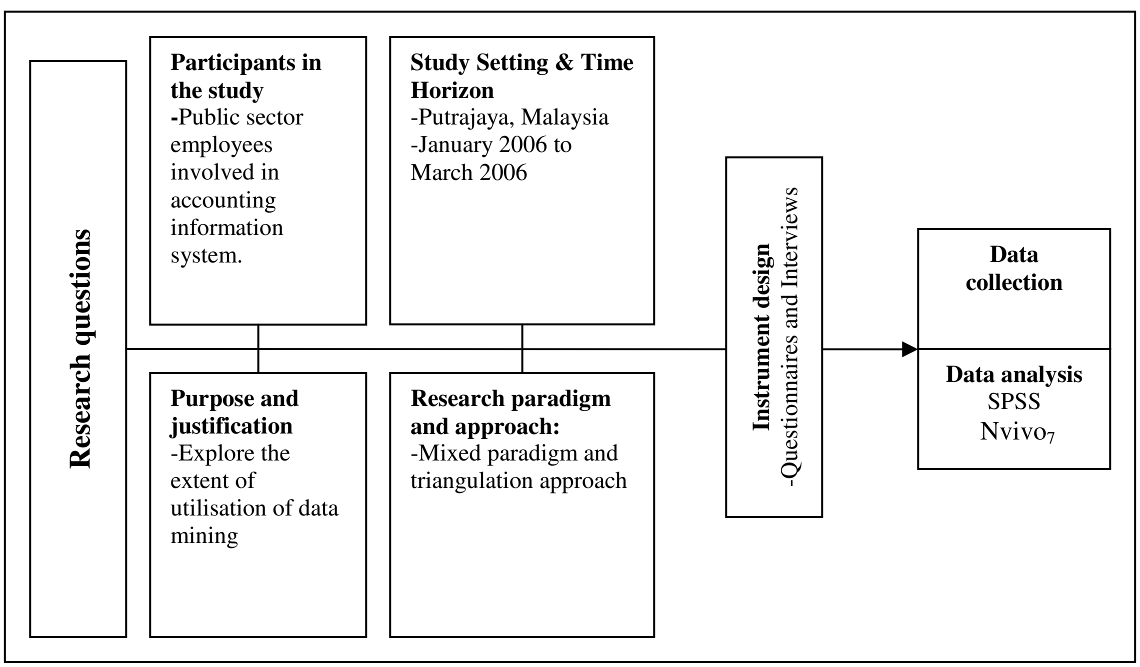
2: In the operation of accounting information system, how would, or does data mining impact on the effectiveness of public sector decision making in Malaysia?

3: Is the ability to utilise data mining techniques one of the important criteria in assessing the performance of Accounting Information System in the Malaysian public sector?

4: What model would allow the Malaysian public sector to best apply data mining techniques to ensure high quality of information within the Accounting Information Systems?

Figure 4.1 below provides the research design to be adopted within this study. The design commences by specifying the research questions to be analysed as posed earlier, identifying the participants, the setting of the study and it's time horizon, purpose and justification of the research before discussing the research paradigm and the approach taken. Each of these parts of the research design will discussed in turn.

Figure 4.1: Modelling the research design adopted in this Study



(Source: adapted from Cavana *et al.,* 2001)

4.2.1 Participants in the study

The participants in this study are individuals within the Malaysian public sector. The role of participants selected was in accounting, finance, auditing or a task related to the accounting information system. In order to identify all possible respondents the names and job roles were identified from the web pages of the relevant departments within the Ministry of Finance, Accountant General Department and Auditor General Department. They were chosen as the target respondent as they are believed to represent the major accounting information system stakeholders within the organisation and could be expected to have a better understanding of the information issues within each organisation. To ensure full coverage of potential respondents, a current list of employee's names and email addresses obtained from each department's website is used as the basis for distributing the questionnaire. A questionnaire was distributed to each of these people.

This study is of individuals within their work environment (Babbie, 2005, Cavana *et al.,* 2001). Within this study, individuals are to be surveyed and interviewed to address the basic research problem in the identification of the level of awareness, and the readiness levels of Malaysian civil servant staff toward data mining technologies. The study also seeks to discover the extent of implementation of these technologies, the influential factors and reasons for or for not utilising such technologies in the organisation or department. While the data will be collected from individuals it will be possible to aggregate the quantitative results to make comparisons between departments for example, which then treats the department as the unit of analysis. The individual will be the unit of analysis for this study.

4.2.2 Study Setting and Time Horizon

The setting selected for the study was Department of Accountant General, Department of Auditor General, and Ministry of Finance in Malaysia. Most of the selected respondents were located in Putrajaya, an administrative City of Malaysia. This study through the use of surveys and interviews was undertaken in a non-contrived setting with no interference with the normal work routine. The respondent was contacted prior to the distribution of questionnaires. For those respondents who are not located within Putrajaya area, questionnaires packages were mailed to them. Respondents who indicated that they agreed to be interviewed were contacted and set a time for interviews. All the interviews were undertaken at their respective office. The process of distributing, collecting the questionnaires, and interviews begins in late January 2006 concluding at the end of March 2006.

4.2.3 Purpose and justification

The study sought to gain an understanding of the extent of utilisation of data mining technology within the public sector in Malaysia. The extent of utilisation is expected to be impacted on by factors such as the level of awareness of data mining technology, and the readiness to implement technological solutions. This study explores the utilisation of data technology as well as the level of awareness and readiness towards this technology. As there is very little published research on data mining technology usage in Malaysia, and almost no studies of data mining technology usage within AIS in the public sector, the study was designed to be exploratory. The study sought to discover the level of awareness by management of data mining concepts, firm readiness to accept and implement data mining and management's perception of the impact of data mining on their current accounting information systems (AIS). This study will assist in filling this gap in the literature.

4.2.4 Research Paradigm and approach

Paradigm

The present study was not fixated on a single paradigm. Veal (2005) argued that different paradigms can coexist in the same study and complement one another. As cited by Mingers (2003) from the work of Orlikowski and Baroudi (1991) they concluded that the vast majority of information system research adopts a mixed paradigm approach. As far as this study is concerned it adopted a mixed paradigm approach.

A positivist view was adopted in this study based on its assumptions on particular social reality, such as attitudes of readiness toward data mining and their satisfaction toward accounting systems. All those social reality viewed as objectively measured through adopting a positivist paradigm via the use of scientific method on basis of the facts and observations (quantitative nature) (Cavana *et al*., 2001, Ikart, 2005, Veal, 2005). Quantitative strategy adopted in the questionnaires is always associated with positivist research (Henn *et al*., 2006).

Apart from imposing a model of positive reality, views of the reality based on the perception of the participants involved was also considered. This is because it is believed that it is more likely that participant's experience physical and social reality in different ways. The study is also interested in gaining some information about the meaning or reasoning behind participant actions in adopting data mining for example, their knowledge and understanding about data mining, how they think about technology advancement in their jobs. This information will rely on their explanation or behaviour (Veal, 2005) and therefore critical/interpretive paradigm was also adopted in this study to gain all those information.

It was assumed that by combining those two paradigms of research it would produce rich and reliable results. A positivist view was taken in initial stage of the study with quantitative data collection. This was followed by a number of interviews leading to an interpretative analysis in order to gain a deeper understanding of the issues. The next section discusses the appropriateness of the approach and methodology selected for this study which combining quantitative and qualitative methods of data collection.

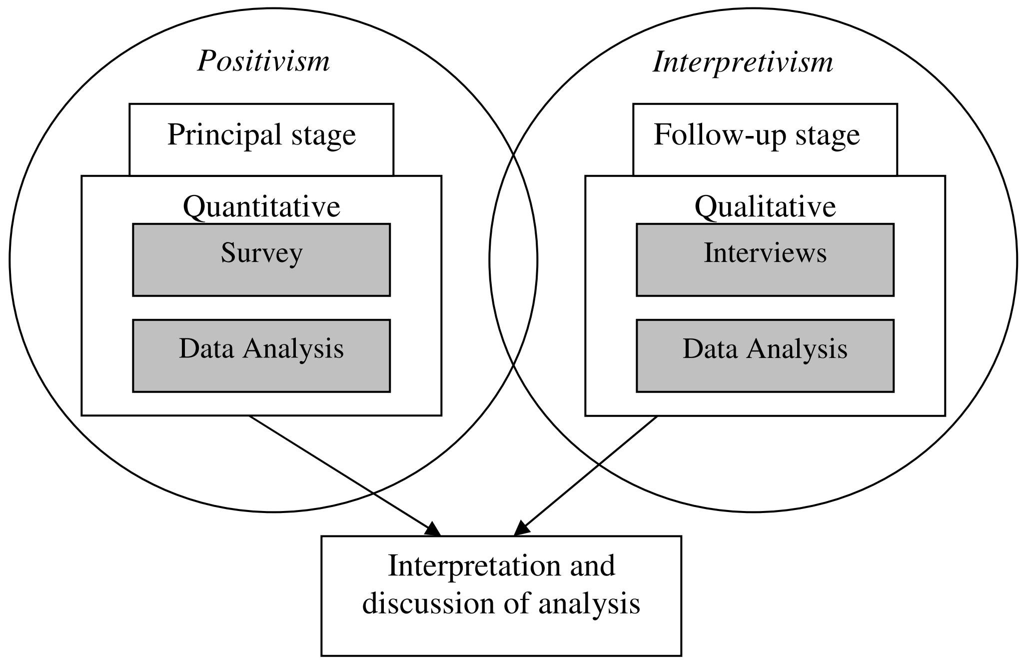
Approach

In this study a triangulated approach was undertaken to the collection of data. The intention was to collect both survey data (quantitative) and interview data (qualitative). While the survey data would provide a basic understanding about what is happening in regard to data mining such as awareness of, and attitude toward data mining, and software currently in use within the department, interviews were intended to enrich the data by adding insights into the way participants felt about, thought about and saw data mining within their work environments. It sought to discover underlying meaning and patterns in greater depth in terms of perceptions of interviewees towards technology readiness impacting on their everyday work activities, the type of training available to upgrade skills, their views on data mining, it's utilisation and future in the department, and opinions about the best data mining model that they believe might suit the public sector. As Miles and Huberman (1994, p. 40) argue '…we have to face the fact that numbers and words are both needed if we are to understand the world'. By using triangulated measurements, different methodological viewpoints can be integrated to increase validity and confidence of the researchers (Bryman, 2006). This is because it allows us to measure the views of stakeholders 'from two different positions' (Veal, 2005, p. 39).

The adoption of mixed method research has grown in popularity in recent years. Henn *et al.*, (2006) note that there are an increasing number of social researchers who recommend the adoption of more flexible approaches to research method in studies rather than adherence to either a positivist-quantitative or an interpretive-qualitative style of research. A justification for this view rests on the grounds that it helps to facilitate a more valid and holistic picture of society than that which could be acquired by remaining true to only one set of methods (Henn *et al.,* 2006). The mixed methodology approach can be used to verify the quality of the information being collected and its validity and reliability (Henn *et al*., 2006, Lancaster, 2005, Sekaran, 2000, Morgan, 1998, Brewer & Hunter, 2006). That is, it better enables the researcher to understand what is happening in the real world.

The present study was carried out into two stages (principal and follow-up): 1) A quantitative stage, employing a mail survey which basically influenced by the positivism paradigm, and 2), a qualitative stage, employing interviews, influenced by an intepretivism background (shown in figure 4.2 below) .

Figure 4.2: Approaches taken in data collection and analysis



4.2.5 Instrument design - questionnaire[9]

Self-administered questionnaires were adopted for the quantitative part of this study. There is no right or wrong way to set a questionnaire up but wordy and poorly designed questionnaires should be avoided as they may result in biases, non-compliance and frustration (Nardi, 2006). Preparation of the questionnaire involved many drafts in order to seek the information required but also to avoid possible problems. Self-administered questionnaires have the advantage that they may be complete in the participants own time. Nardi (2006) summarized the benefits derived from a self administered questionnaire: (a) Where the number of variables (values or response categories) would be too numerous to read either at an interview or over the telephone, (b) When non observable attitudes and opinions are being investigated (c) Where the characteristics of a large population are being described, and (d) When studying behaviours that may be more stigmatizing or difficult for people to tell someone else face-to-face.

[9] A copy of questionnaire is shown in Appendix One

The design of the questionnaire of this study adopted several sources of data, including previous instruments developed by other researchers and the research framework developed from the relevant literature. Most of the questions were in closed form using a Likert-type scale[10]. Factors in evaluating AIS performance, readiness toward technology, factors influencing the organisation to employ data mining, reasons for not implementing data mining, perception of the impact by data mining to organisational performance were all scored on five-point numerical scale from 1=strongly disagree to 5=strongly agree. Itemized rating scale was also developed for few questions. For example, scale from 1=poor to 5=excellent was used for question as to rate the actual performance on important factors for quality AIS. There is also similar scale 1=seldom to 5=very often was used for question requesting to indicate frequency of AIS data were used in particular areas. The written questionnaire (see Appendix 1.2) consists of 24 questions (in 5 sections/categories).

There was a half page empty space at the end of the questionnaire to give respondents an opportunity to express anything else that they would like to add. Lastly, there was a separate form attached to the questionnaire to be filled by respondents willing to be interviewed.

a) Variables Identified Within the Questionnaire

In the process of developing the instrument, there were several variables determined. These variables were classified into five categories: organisation's accounting information systems, data mining readiness, implementers/non-implementers of data mining, perception on data mining impact, and demography. Each of these are shown in Table 4.1 and discussed below.

[10] Likert scales are commonly used to measure attitude, providing 'range of responses to a given question or statements. It has become practice to assume the Likert-type categories constitute interval-level measurement (Jamieson, 2004).

Table 4.1 Categories and variables in questionnaire

Category	Variables identified in a questionnaire
1	Organisation's Accounting Information Systems 1.1 Satisfaction on current system 1.2 Specific software packages uses 1.3 Quality AIS data and performance 1.4 Frequency using data from AIS in certain areas 1.5 Evaluation of AIS performance
2	Data Mining Readiness 2.1 Awareness about data mining 2.2 Level of optimism, innovativeness, perception toward easiness and usefulness of the technology
3	Variables determined for implementers and non-implementers 3.1 Utilisation of data mining tools 3.2 Number of year the tools being use 3.3 Influencing factors which makes organisation implement the technology 3.4 Factors or reasons on why not implementing it 3.5 Intention to use data mining
4	Perception of data mining impact 4.1 What perception on the impact could data mining give to the performance of AIS 4.2 Does decision making process affected by data mining implementation?
5	Demographic details 5.1 Personal information about respondent 5.2 Size of the organisation 5.3 Knowledge about data mining

- The first category looks at characteristics relating to the current accounting information system operating within the department. Respondent's satisfaction, software currently in use, perceptions of quality and performance of the AIS, degree of reliance on the accounting information system (AIS) data and how respondents evaluate their systems performances are investigated. Reliance on AIS data was based on the frequency it was used for - planning and budget, decision making, performance measurement, and cost control. In terms of performance of the accounting information systems four factors are identified - accuracy, timeliness, completeness, and consistency.

- The second category aimed to examine the awareness and readiness toward data mining. Questions included were intended to gauge general levels of awareness of data mining and respondent behaviours and beliefs toward the adoption of technology in particular data mining. These questions were identified from the Technology Readiness Index (TRI)'s survey, Data Mining Readiness Index (DMRI) and Technology Acceptance Model (TAM)

(Parasuraman 2000, Dahlan *et al.,* 2002 and Legris *et al*., 2003). Questions were also designed to measure optimism, innovativeness, *usefulness* and *ease of use*.

- The third category of variables classified adopters and non-adopters of technology and considered the level of awareness of data mining within the organisation and factors influencing adoption/not adoption of the technology. Lists of factors/reasons believed to influence the organisation to adopt data mining within the organisation were identified. These factors/reasons were *organisational issues* (Dahlan *et al*., 2002, Chang *et al*., 2003, Calderon *et al.,* 2003), *technological issues* (Syed-Ikhsan & Rowland, 2004a, 2004b, Dahlan *et al*., 2002, Ndubisi & Jantan, 2003, Legris *et al*., 2003, Riemenschneider *et al.,* 2003, Amoako-Gyampah & Salam, 2004), *human resources issues* (Dahlan *et al*., 2002, Feelders *et al.,* 2000) and *external factors* (Ang *et al*., 2001).

- The fourth category examined the impact data mining would have on the performance of department as perceived by the respondent.

- Finally, the fifth category sought demographic information about the respondents (gender, age group, level of education, work experience, job function, levels of responsibility, department size and knowledge about data mining).

b) Coding of measurement scales

Construct measurement scales and coding were developed (Table 4.2). There were 48 scale items in the questionnaires including performance of AIS (4 items), awareness and understanding (3 items), data mining readiness (10 items), utilisation (1 item), influence factors (10 items) and reasons (9 items), intention to utilise (1 item), data mining impact (8 items) and ability to utilise data mining tools (2 items).

Table 4.2 Coding of measurement scale

Construct	Code	Statement/Items
AIS performance	AccPerf	Performance – accuracy of data
	DatePerf	Performance - up-to-date data
	ComPerf	Performance - completeness of data
	ConPerf	Performance - consistency of data
Awareness and knowledge	UsedTerm	Use of the term data mining in the department?
	OtherTerm	Is another term used to describe data mining
	DMknow	Rank your knowledge about data mining?
Optimism	Opt1	Technology gives me greater control over my daily work
	Opt2	Products and services that use the newest technologies are much more convenient to use
	Opt3	I prefer to use the most advanced technology available
	Opt4	Technology makes me more efficient in my occupation
	Opt5	I think it would be very good to use data mining technology for analysing accounting data in addition to current methods
Innovativeness	Innov1	I keep up with the latest technological developments in my areas of interest
	Innov2	I find myself having fewer problems than other people in making technology work for me
	Innov3	I am always open to learn about new and different technologies
Perceived ease of use	Easy	It is easy to learn how to use technology
Perceived usefulness	Useful	Overall, I find the technology useful for any task I need to accomplish
Utilisation of data mining	UtiliseDM	Based on the definition, does your organisation utilise any data mining tools?
Organisational Influences	InfluenOrg3	Full support from top management
	InfluenOrg10	Sufficient financial resources
Technological Influences	InfluenTech1	Adequate technical support from vendors
	InfluenTech2	Compatibility of software with existing operating systems
	InfluenTech6	Up to date ICT infrastructure
Human resources Influences	InfluenHR4	Effective and adequate training for staff
	InfluenHR5	Technology aware staff
External Influences	InfluenExt7	Changes in management trend within private sector
	InfluenExt8	Directives from politicians
	InfluenExt9	In attempt to ensure public accountability
Organisational Reasons	NotImpOrg5	Lack of top management support
	NotImpOrg4	Costly to implement new technology
	NotImpOrg8	Lack of management policies
	NotImpOrg9	More pressing problems
Technological Reasons	NotImpTech1	Satisfied with current analysis method
	NotImpTech6	Difficult to select appropriate software
	NotImpTech7	Too complex and time consuming
Human resources Reasons	NotImpHR2	Lack of expertise to implement data mining
	NotImpHR3	Lack of awareness about data mining
Intention to adopt	IntenToAdopt	Does your organisation intend to adopt data mining?
Impact of Data Mining:		
AIS performance (PImpctAIS)	Impct_AIS1	Lower transaction cost
	Impct_AIS2	Improve the quality of information derived from AIS
	Impct_AIS3	Increase AIS performance
	Impct_AIS4	Improve the quality of transaction data
	Impct_AIS5	Reduce cycle time of the department
Decision making (PImpctDecM)	Impct_DecM1	Meet the information needs for the decision making
	Impct_DecM2	Provides decision support in decision making
	Impct_DecM3	Contribute to the speed of decision making
Ability to utilise data mining (AbilityToUtiliseDM)	AisPerfATU	The systems implement new data analysis tools (such as data mining)
	AisPerfDW	The system has an effective data management approach such as, centralised database and data warehouse

c) Construct Reliability, and validity of the instrument

An assessment of the reliability of the constructs and the validity of the instrument were conducted to establish the reliability and validity of the instrument. The means of the construct measures will be computed to investigate internal consistency and validity.

d) Pre-testing

To identify any remaining issues with the test instruments pre-testing was undertaken (Hunt *et al*., 1982, Presser & Blair, 1994, Babbie, 2005). Pre testing was intended to identify whether there were any ambiguous or unanswerable questions, to identify whether the wording or layout could be improved, whether the meaning the researcher believed was associated with a question was how others perceived it.

A draft of the questionnaire was sent electronically to academics in University of Tasmania and Kolej Universiti Sains dan Teknologi Malaysia. Academics pretended to be respondents at a school seminar (School of Accounting and Corporate Governance) to assist in testing the instrument. Staff comments and suggestions were used to revise the instrument in terms of presentation, readability, validity and to reduce the number of items. It also confirmed that the estimate of time required was reasonable and the questions were suitable for the intended participants. Changes and additions were made to the instrument which included:

- Refining of some of the questions to increase clarity and remove ambiguities,
- Reducing of some redundant items to achieve concise and precise, and
- Changes to some of the measurement scales.

The questionnaire was then submitted to and approved by the Human Research Ethics Committee, University of Tasmania. As the questionnaire was originally prepared in English, translation of the questionnaire was required. Although English is generally used within Malaysia, it is sometimes easier for respondents to respond in Bahasa Malaysia. A two language version of the questionnaire was produced to provide respondents an option to choose which one they preferred. To ensure the translating version was equivalent to the original, it was first translated to Bahasa Malaysia. This version was then translated back into English by someone else who is also fluent in both languages. A final comparison was made and the two versions of the questionnaire were ready to administer.

4.2.6 Instrument design – the interview guide (Protocol)

The interview questions were designed to supplement and enrichment the quantitative data collected. The interview schedule was divided into four parts (see Appendix Two):

1. General information about interviewee's background in terms of education, working experiences, roles in the organisation and roles relating to the accounting information.
2. Questions relating to the status of the accounting information system (AIS) currently implemented in the organisation.
3. This section explored the level of readiness to implement and awareness of data mining techniques, and the interviewee's perception of the role and importance of information technologies in their everyday work activities.
4. The questions focused on whether data mining technologies were utilised in the respondents department. Adopter and non-adopters of data mining technologies were identified. Questions for non-adopters explored the reasons for not having such technology, approaches taken to the analysis of accounting data, and intention to consider data mining software in the future. While for adopters, the questions will mainly asked the reasons and factors that drove to the department to implementation, the impact of data mining on AIS performance and the decision making process.

4.3 Data collection

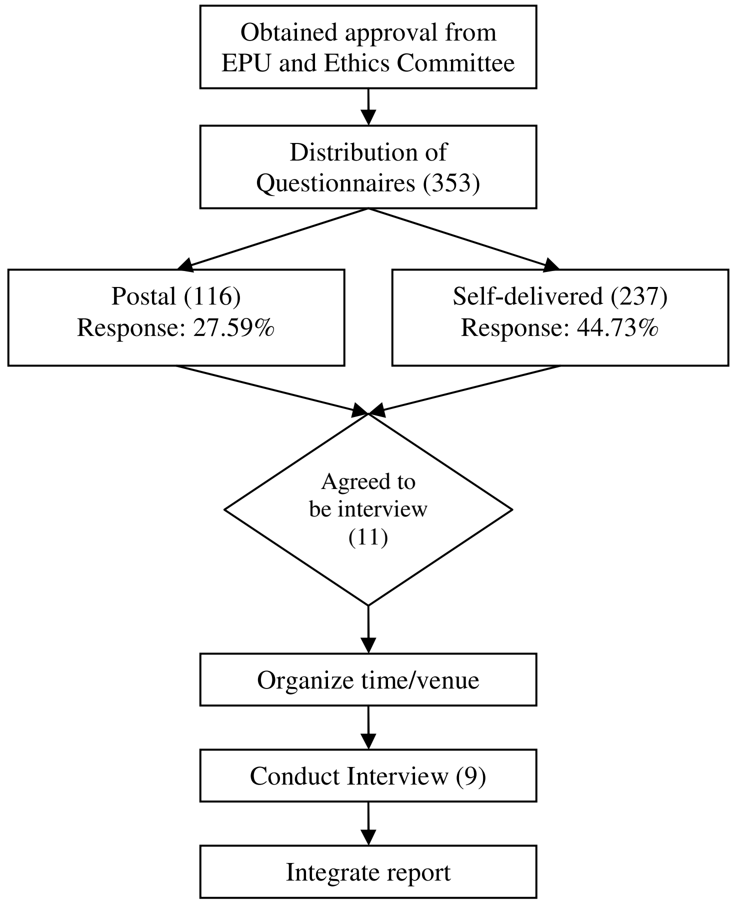
A triangulated approach to data collection was adopted in this study utilising a mail and hand delivered survey followed by a number of semi structured interviews. The interviews were intended to improve the richness of the data already collected from the surveys.

In preparation for data collection a number of formalities had to be met. The approval of the Malaysian Government to undertake the work was required, and the ethics committee of the University of Tasmania had to approve the survey and interview instruments to be used. Figure 4.3 below illustrated the data collection procedures taken for this study.

Approval from the Malaysian Government is sought through the Economic Planning Unit (EPU), Prime Minister Department. This unit is responsible to regulate and co-ordinate research conducted in Malaysia by foreign researchers and Malaysian nationals from institutions and/or organisations overseas. The process for approval requires justification for the research project and discussion how the research would contribute to the wellbeing of the departments being studied in the future. Upon approval researchers are supplied with a photo ID research pass which is valid for a three month period.

Prior to that, approval from the University of Tasmania ethics committee was also obtained. This was a minimal risk application with final approval taking eight weeks. Upon approval from both Economic Planning Unit and University of Tasmania ethic committee, the survey questionnaires were prepared for mail-out and then distributed to the selected respondents.

Figure 4.3: Flowchart in conducting survey and interviews



In the survey, this study adopted closed questions with a number of open-ended categories offering the opportunity for extended responses by respondents. Open-ended questions were used to gain information about specific software in use, to capture functions involving the use of accounting data and to capture terms used as synonyms for data mining.

The survey was chosen to be the primary method of data collection as it is a means to collect information at a reasonable cost while maintaining anonymity (Sekaran, 2000). This method has also been successfully used by previous researchers in this area in Malaysia. Zain *et al.,* (2003), used a mailed self-administered questionnaire in their study on the use of information technology for organisational agility in Malaysian firms, Wah and Abu Bakar (2003) used the same method to investigate the status of data mining in practice in Malaysian banking sectors. Dahlan *et al.,* (2002) in their investigation on firm's readiness to adopt data mining technologies also adopted this method of data collection. One of the advantages of this type of survey is that participants have time to review the questions and respond in their own time with little pressure. In this way it was hoped more thoughtful responses would be made.

Before the packages of questionnaires were sent/delivered, an initial email was sent to all potential respondents to advise them that they would receive a package of questionnaires in coming weeks. For the postal group, the email advised them that the questionnaire packages would include a self addressed stamped envelop for them to reply. Hand-delivered groups were advised that the officer in charge of their department would distribute the packages, and on completion they were to be returned to this officer. Initial contact was made with the officers in charge of the departments requesting their assistance. Each agreed to assist in distributing and collecting the questionnaires within their departments. Frequent phone calls and email contact was made between the researcher and these officers to determine the status and number of questionnaires received.

The survey was conducted between January and February 2006. The respondents were assured of confidentiality concerning their personal information. Neither department names nor identification of individuals were used by anyone other than researcher's supervisor and researcher. The survey packages included a cover letter asking for their cooperation, a postage-paid return envelope, and a copy of the questionnaire. The cover letter explained the objectives of the study, a guarantee of the confidentiality of the respondent, an estimate of time for the respondent to complete the questionnaire and the expected date for the respondent to return the completed questionnaire. It also thanked the respondents for their time and effort in participating in the study. The cover letter was printed on the University of Tasmania letterhead. It includes the name and contact information of the researcher and signed by both researcher and primary supervisor of this PhD project. The contact person for any ethical enquiries was also provided should there have been concerns of an ethical nature[11]. In an attempt to increase respondents' cooperation with the survey, a copy of approval letter from Economic Planning Unit, Prime Minister's Department and a copy of a research pass were also included in the survey packages.

Three hundred and fifty three questionnaire packages were distributed in 2 batches through ordinary mail and self-delivered to prospective respondents. There were 116 survey packages mailed to various locations according to their offices situated across Malaysia. While the remaining questionnaires (237 questionnaires) were distributed to the Accountant General's Department with the assistant of the Senior Assistant Director, and to Ministry of Finance with the assistant of the Assistant Secretary at the Administration Section. There was a total of 190 questionnaires distributed to the Accountant General's Department and 47 to Ministry of Finance. A specific date was agreed for the researcher to come and collect the questionnaires. After approximately three weeks from the initial mailing and distribution, a reminder email was sent out to all respondents. An email thanked the respondents who had already returned their questionnaire and encouraged others to respond as well. For postal questionnaires, the collection center was at Jabatan Perakaunan dan Kewangan, Fakulti Pengurusan dan Ekonomi, Kolej Universiti Sains dan Teknologi Malaysia (now Universiti Malaysia Terengganu). Setting up a collection center within Malaysia assisted in reducing postal cost in comparison to a mail out from an overseas address within Australia. An overall response rate of 39.94% was achieved. The response rate for self delivered packages was greater than for postal responses (44.73% compared to 27.59%).

The next stage of the investigation was to conduct interviews with those respondents who were identified and were willing to be interviewed. Personal interviews have the advantage of allowing flexibility in adapting and clarifying the questions (Sekaran (2000). Sekaran (2000) also suggested that this method would incur more cost, time and having a geographical limitations. The interviews were viable for this study however, because the number of interviews was small, designed to supplement the survey data and assist in enriching this data and were undertaken in a confined geographic area.

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[11] See Appendix 2.1 for a copy of the cover letter.

An abbreviated version of questions used in the interviews[12] and consent form[13] were sent to the interviewees before conducting the interviews. The interviews were tape recorded, with the agreement of the interviewees, and notes taken during the interviews to ensure accuracy in recording and transcription of the interviews. Nine interviews were undertaken, all interviewees were located in the same geographical area.

Interviews were semi-structured to offer the greatest opportunity to explore issues. This allowed the interviewer to vary the sequence of questions, explain meanings, add additional words or change the wording as appropriate. The way of asking and the sequence of the questions were determined by the progress of the interview and as various issues arose and were explored. Questions were prepared in advance to act as a guide and to ensure that within a reasonable time all applicable questions were asked and discussed. All interviews were conducted in real-time conversation between interviewer and respondent to discover and to gain additional information regarding respondent's perceptions, experiences, awareness and opinions about data mining technologies within their department.

4.4 Rules on Ethics and Confidentiality

Before conducting the interviews and the questionnaire survey, the approval of the Ethics Committee of the University of Tasmania was obtained in 2005 to preserve the rights, liberties and safety of the participants. In addition, an information sheet, including the name of the University of Tasmania and the name of the school, was prepared to explain the purpose of the study and the ethical rules and was given to each participant, attached to the questionnaires. The participants were informed that under the ethical rules, they were participating voluntarily and no risks, such as psychological, moral, legal or other risks, would occur with them. It advised the respondent to refer any queries or complaints they may have about the way the study was conducted to the Executive Officer of the Human Research Ethics Committee

[12] Appendix three
[13] Appendix four

(Tasmania). A telephone number, an email was provided on the cover letter to that effect[14].

Personal interviews were conducted with the consent of the participants. Interviewees selected had indicated their willingness to participate in an interview on a form attached to the survey questionnaire. Selected interviewees were provided with an interview information letter, consent form and an indication of the questions to be explored at the interview. Interviewees were advised they could withdraw from the research project at any time. Once again, before conducting the personal interviews, the participants were fully informed as to the objectives of the research and the ethical rules.

Completed questionnaires of the survey and transcripts of the personal interviews are kept in a secure place at the University of Tasmania under the researcher's control and are available only to the researcher and supervisors.

4.5 Data analysis techniques

4.5.1. Quantitative data

The quantitative data was analysed using the Statistical Package for the Social Sciences SPSS version 14. A range of statistical procedures are adopted to explore the research questions posed and to test the hypotheses. Initially descriptive analysis was undertaken to explore the results prior to in-depth analysis undertaken to test the hypotheses posed. In identifying suitable analytical techniques statistical textbooks were consulted. These texts suggest and identify appropriate statistics for difference types of research questions and research hypotheses (see Leech *et al.,* 2005, Nardi, 2006, Carver & Nash, 2005, Colman *et al.,* 2006). Nardi (2006) in particular suggested the statistical decision tree[15] which is very helpful in deciding on what statistical methods would be most appropriate for this study. Most of the data

[14] See Appendix 1.1, 2.1.
[15] See Appendix Five: Statistical Analysis Decision Tree

collected adopted a 5 point likert-scale. Responses to several likert items are summed and averaged, they are treated as interval data measuring a latent variable[16].

a) One Sample T-Test

This t-test is adopted to determine the significance of the difference between the mean of a sample of scores and some specified value. In this study, 3 (midpoint of the likert scale) was used as a test value. Three represents a neutral point, for example between agree and disagree, therefore if the mean value falls below the test value, this suggests that the respondent did not agree with that particular item, or question. This test is to be adopted in the process of investigating research questions one, two and three, and in testing hypotheses one and two. The t-test analysis offers insights into five questions:

1) Do respondents agree with the statements representing optimism, innovativeness, easy to use and usefulness in their readiness to accept data mining?
2) Do adopters agree to that technological, organisational, human resource, and external issues are important to the decision to employ data mining?
3) Do non-adopters agree that technological, organisational and human resources issues offered reasons for not utilising data mining?
4) Do respondents agree to the statements reflecting the impact data mining could have on the accounting information system and the decision making process?
5) Do respondents agree that the ability to utilise data mining is important in the process of assessing the performance of AIS?

[16] Although there is argument that such treatment can be seen controversial (see, Jamieson, 2004). It also has become common practice to assume the likert-scale categories constitute interval-level measurement.

b) Independent Samples T-Test

This type of *t-test*[17] has been used to test whether there is a significant difference between two groups of respondents. The test is used to compare the means of the two groups to assess whether there is a significant difference between the groups. For example, was there a difference between respondents who were mailed questionnaires as compared to those who received a hand delivered questionnaire? Are there gender differences between in terms of readiness toward data mining? In this study these tests are used to test the validity of survey instrument and to test hypothesis four.

c) One-way Analysis of Variance (ANOVA)

ANOVA[18] is undertaken to assess whether there is a significant difference among several independent group means. In general, the test is similar to t-test but designed to determine the significance of the differences among three or more (rather than only two) group means. In this study, analysis of variance (ANOVA) mainly intended to offer responses to the questions:

1) Is the readiness toward data mining significantly different among different levels of education, different groups of adopters, different job functions, different levels knowledge about data mining, and working experience in AIS[19]?
2) Are there any different between respondents who have more knowledge about data mining and who has limited knowledge about it on their perception of the impact of data mining to AIS and Decision Making?

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[17] The test is used to test for a significant difference between the means of two independent or unrelated samples of scores. It can be used with groups of unequal size. (Colman *et al.,* 2006)
[18] It was done by partitioning the total variance in the dependent variable in effects due to different levels of the independent variable (Colman *et. al*., 2006)
[19] As also suggested by Francis (2004) and Nardi (2006) when there are more than two categories for example as for this study as concern, the level of education, we should use analysis of variance. A technique that asks whether the differences within a category are larger or smaller than those between those four levels of education.

It will be adopted to test hypotheses five, six, seven, eight and nine examining the differences of means (readiness) among those categories of independent groups. The test will seek to assess whether there is any difference between the levels of independent variables on readiness toward data mining technology.

d) Association Analysis (Correlation and Cross Tabulation)

Measurements of association via correlation indicate the strength and the direction of the relationship between pair of variables. There are two types of measure: measures of linear correlation using interval variables and measures of rank correlation using ordinal variables (Bryman & Cramer, 1994).

A linear correlation analysis was adopted to explore the relationships between statements representing the ability to utilise data mining in the performance of Accounting Information Systems. As the variables are interval, the Pearson product moment correlation is adopted. This is the most well-known approach of expressing the effect sizes in terms of strength of association (Leech *et al*., 2005). 'Using Pearson *r*, effect size are always less than 1.0, varying between -1.0 and +1.0 with 0 representing no effect and +1 or -1 the maximum effect' (Leech *et al.,* 2005, p.55). Pearson *r* normally used in measuring or testing associational type of questions or hypothesis which both variables under study are normal/scale in measurement. For the purpose of this study, the interpretation of the strength of a relationship (effect size) includes: .10 to .30 as small, .30 to .50 medium, .50 to .70 large and $\geq$ .70 very large strength of relationship[20].

While in the case of ordinal variables, second type of correlation analysis is appropriate to be used. Spearman's rank order correlation coefficient or *rho* was adopted for investigating the correlation between ordinal variables (Colman *et al.,* 2006). It will be adopted for measuring the correlation of data mining knowledge with the intention to adopt data mining and with data mining terminology used.

[20] Leech *et al.,* (2005) offer a discussion on interpreting size effect sizes which mostly referring to Cohen's (1988) works.

Unlike the Pearson *r* (parametric tests), Spearman's rank order correlation is non-parametric test method. This is because sometimes we cannot assume normality in the data and also the data sometimes do not lend themselves to computing a mean (in this case the variables are ordinal). Nonparametrics is advised to be used in this situation (Carver & Nash, 2005). In the cross tabulation procedure, *Gamma* was also used to measure the strength of association which also indicates the direction of association between two ordinal variables (Babbie *et al.,* 2003).

For this study the correlation analysis is intended to offer responses to the following questions which relate to hypothesis three and ten respectively:

1) Is knowledge about data mining possessed by respondents correlated with the intention to utilise that technology?
2) Is there a correlation between an ability to utilise data mining with the performance of AIS?

4.5.2. Qualitative data

There are two major approaches commonly utilised in analysing qualitative data, namely content analysis and grounded theory (Lillis, 1999). As discussed briefly by Cavana *et al.,* (2001), the general definition of content analysis is the process of identifying, coding and categorising the primary patterns in the data. This general definition was used based on the work of Patton (1990) as opposed to the other works (Krippendorff, 1980) which refer to content analysis as a statistical analysis of key word or phrase occurrences. This approach utilises a set of procedures to make valid inferences from text. Lillis (1999) also refers to content analysis as a quantitative technique limited to the manifest characteristics of text, such as the number of occurrences of words, or the number of words relating to particular themes.

This study adopted the general definition of content analysis used by Patton (1990). The application of content analysis in this study is to qualitatively examine latent characteristics in the data such as classifying themes in elaborated responses. The primary intention in using the qualitative data was to corroborate quantitative data collated from questionnaires. In this study qualitative data was examined through Nvivo $_7$.

a) The analytical method

The process to analyse the qualitative data begins with transcribing all recorded tapes into written form and transfer this to Microsoft word. The qualitative data for this study is in the form of transcribed text of 9 semi-structured interviews. Additional written comments on the questionnaires were also considered. Veal (2005) suggested that it can be great value to produce complete verbatim (word-for-word) transcripts of interviews. While the process of transcribing those interviews is laborious, Veal (2005) argued that complete verbatim transcripts could be used to analyse in a more methodical and complete manner compare to just taking notes.

All data was exported to the Nvivo $_7$ program to allow the systematic restructuring of the sources and the display of information under similar themes or topics. The arrangement of reproducing text files under the particular themes enables the researcher to answer the research questions at hand. The following procedures were taken in the process of analysis.

Predetermined themes were set up – for example, satisfaction level with the current system, readiness to accept new technology, awareness of data mining terms, perception of data mining impact, intention to adopt, factors and reasons for adoption, and best possible data mining model can be implemented in the public sector. Data which contains short blocks of text, quotations, and phrases from the entire data were transferred into new file under specific themes. The aim was to classify all related text to at least one thematic code.

Once the text has been classified under related themes, these new files will be used to corroborate and enrich the quantitative results. These quotations, characteristics, and attitudes were integrated into the analysis converge the results of quantitative and qualitative analysis.

4.6 Conclusion

This chapter offers an overview of the research design and approaches to be adopted in responding to the research questions and to the hypotheses posed in this study. The data collected from the returned questionnaires is presented and discussed in the next chapter.

Chapter 5

Results, Findings and Narrative Analysis

5.1 Introduction

In reporting the results of this study the level of awareness, and readiness amongst public sector employees towards data mining technologies in Malaysia, in particular, related to the accounting information system are explored. In this chapter the descriptive information collected and the research questions are discussed.

5.2 Response Rate

In this study survey questionnaires were both mailed and self delivered. An overall response rate of 39.09% was achieved from 353 survey packages delivered to respondent. Usable response rates from the mailed survey were 27.59% and for self-delivered (personally deliver and collect) were 44.73%. The ability to hand deliver surveys appears to have encouraged a significantly higher response rate. Table 5.1 below shows the summary of percentages of responses.

Table 5.1 Respondents and response rate

Total	Sample	Respondents	Percentage Response
Self delivered	237	106	44.73
Postal	116	32	27.59
Total Usable responses	353	138	39.09
Declined to answer[21]		3	
Actual responses	353	141	39.94

The response rate is acceptable. For example, it has been found that response rates tend to be lowest for mailed questionnaires and it is not unusual for researchers to receive only 20 to 30 percent of the questionnaires and use these responses for analysis (Wilson, 2003, Nardi, 2006). Follow-up email contact and telephone calls

[21] Three questionnaires were returned with an apology for not responding to the survey. In the case of one of the respondents it was indicated that the department did not utilise an accounting information system, the second indicated that they feared their response would be misleading to the intent of the research, and the third felt that the study was not suitable in public sector.

were made in an effort to increase the rate of response. To further explore, nine respondents were selected to be interviewed with the intent to enrich the data collected in the quantitative part of the survey. Eight interviews were conducted in Putrajaya and one in Kuala Lumpur. Respondents' interviewed comprised 5 accountants (two head of department included), 3 auditors and 1 information system officer.

5.3 Reliability and Validity of survey instrument

In this section the reliability and validity of the instruments used in this study are discussed. A reliability test was conducted to investigate the internal consistency for the multiple item scales. The key variables used in the statistical analysis are: data mining readiness, influential factors in the adoption decision, reasons for not adopting, the perceived impact of data mining on Accounting Information System, the perceived impact of data mining on decision making and Accounting Information System performance. From that test, presented in Table 5.2 Cronbach's alpha indicates that the scale is reliable which ranging from .825 to .930. In determining the appropriate minimum loadings required for the inclusion of an item within a scale, Igbaria's (1994) recommendation was adopted, that is highly loaded items were retained (.70 is considered to be a high loading since the item explains almost 50% of the variance in a particular construct). In other words, each item in a scale is consistently measuring the same underlying construct. For example, an Alpha value (.901) for items measuring data mining readiness (see Table 5.2) indicated that each item was positively correlated to one another in assessing the readiness construct. Similar pattern was also shown for the other constructs. Therefore we can say that all key scale items for this study are reliable (Francis, 2004) and internally consistent (Leech *et al.,* 2005).

Table 5.2: Reliability test

Variables	Mean	Actual range	Theoretical range	Alpha Cronbach*
Data Mining Readiness	3.998	3.705 – 4.220	1 – 5	.901
Influence factor in decision to utilise data mining	4.128	2.880 – 4.600	1 - 5	.849
Reasons for not utilising data mining	3.449	3.200 – 3.760	1 - 5	.825
Perceived impact of data mining on AIS	3.941	3.704 – 4.111	1 - 5	.871
Perceived impact of data mining on decision making	4.044	4.022 – 4.059	1 - 5	.866
AIS Performance (Accuracy, Up to date, complete, consistence)	3.113	3.008 – 3.338	1 - 5	.930

Note: *conventional values=0.07

Validity refers to whether we are measuring what we think we are measuring (Babbie *et al.,* 2003, Babbie, 2005). If we can show that we are measuring what we say we are measuring, then we have validated the measure. As discussed in the previous chapter, careful efforts were taken to increase the validity of the questionnaires. Although there is no specific test to assess the validity[22], assessment of mean values between two groups of respondents would give some idea that the instrument is working as intended. The test applied answers the question: Is there any difference between the postal group and the self-delivered group. Validity of the survey instrument used for postal group and self-delivered group was assessed by using a t-test technique to compare the mean of each key variable. Table 5.3 below shows that there are no differences between postal group and self-delivered group in term of those key variables because all significance values are above the significance level of 0.05. Therefore, there is evidence that the instrument is valid and it is expected that all the respondents in this study can be representative of the whole selected sample.

[22] There is no foolproof procedure to establish validity, and the validation methods used should depend on the situation. All methods have limitations, inferences about validity cannot be made solely on the basis of quantitative or statistical procedures (see Punch, 2005, p. 98).

Table 5.3: Validity test between groups of respondents

Comparison	Postal vs. self delivered	N	Mean	Std. Deviation	Sig*
Data Mining Readiness (ReadyOverall)	Postal	28	3.9750	.47346	.947
	Self delivered	104	4.0038	.51557	
Influence factor in decision to utilise data mining	Postal	10	4.1700	.37133	.096
	Self delivered	15	4.1000	.55032	
Reasons for not utilising data mining	Postal	8	3.3580	.54370	.902
	Self delivered	17	3.4815	.53491	
Perceived impact of data mining on AIS (PImpctAIS)	Postal	31	3.8903	.53376	.799
	Self delivered	104	3.9558	.54893	
Perceived impact of data mining on decision making (PImpctDecM)	Postal	31	4.0000	.59004	.651
	Self delivered	104	4.0577	.59564	
AIS Performance (Accuracy, Up to date, complete, consistence)	Postal	27	3.2778	.84732	.568
	Self delivered	103	3.0704	.81756	

At the 0.05 level of significance

5.4 Data Characteristics

This section presents the descriptive statistics including characteristics of respondents such as gender, working experience, and educational level. The individual profiles of nine interviewees are also discussed.

a) Demographic data

This section describes the demographic characteristics of the respondents. Within the sample there was almost a gender balance between female and male. Fifty-three percent (73) of respondents were female and forty-seven percent (64) male. Forty-seven percent (65) were above 40 years old. The majority of respondents held an undergraduate degree (73), a master degree (28) and diploma/below (35). Forty-nine percent of respondents had more than 4 years of working experience with AIS. In terms of primary job function, the data revealed that the most of respondents were working in accounting and finance with fifty-one percent of the respondent (69) and thirty percent (41) of the respondents were working with auditing. It was notable that the proportion of middle management was greater (sixty-three percent) than the other two categories (top management and non-management). This characteristic of respondents is summarized in Table 5.4.

Table 5.4 Demographic characteristic of respondents

Category		Frequency	Percentage
Gender	Male	64	46.7
	Female	73	53.3
Age	<30 years	45	33.1
	>30 years <40 years	26	19.1
	>40 years <50 years	55	40.1
	>50 years	10	7.4
Education	Master's degree	28	20.6
	First Degree/equivalent	73	53.7
	Diploma and lower	35	25.7
Experience with AIS	<4 years	68	50.4
	>4 years <6 years	31	23.0
	>6 years	36	26.6
Job function	Accounting and finance	69	50.7
	Information Management	9	6.6
	Auditing	43	31.6
	Others	15	11.0
Job responsibility	Non-management employee	37	27.4
	Middle management	85	63.0
	Top management	13	9.6

b) The individual profile of interviewees

Nine interviews were undertaken consisting of 5 male and 4 female in various age categories between age 26 and above. In the terms of education all interviewees had an undergraduate degree or higher. Two of the interviewees had experience less than 7 years in Accounting Information System while the other seven interviewees have more than 7 years of working experience in Accounting Information System. Three auditor, five accountants and one information systems officer were involved. Interviewees' profile data is summarized in Table 5.5.

Table 5.5: Profiles of interviewees

Profile	Sex	Age	Highest Education	Experience with AIS	Primary Job function
Interviewee1	Female	26-30	Bachelor in computer system	4-6 Years	Information Technology
Interviewee2	Male	46-50	Bachelor in Accounting	> 10 years	Head of Department
Interviewee3	Male	41-45	MBA	4-6 years	Internal Auditor
Interviewee4	Male	> 50	Master Degree	> 10 years	Head of Department
Interviewee5	Male	41-45	Master	> 10 years	Head Auditor
Interviewee6	Female	41-45	Bachelor in accounting	> 10 years	Accounting
Interviewee7	Female	33 years	Bachelor in Accounting	7 years	Accounting
Interviewee8	Female	33 years	Bachelor in accounting	10 years	Accounting
Interviewee9	Male	36-40	Bachelor degree	10 years	Internal auditor

Source: Questionnaire and interview data

5.5 Analysis of Data

5.5.1 Satisfaction on current systems

The level of satisfaction with the current accounting system is discussed in this section. It is believed should staff be happy with the current accounting information system it may make them less willing/anxious to change. In Table 5.6 the majority of respondents indicated that they were satisfied with the current system (57%) although a number recognised that there is a need for some improvement (39%). Only 6 respondents were not satisfied with the current system.

Table 5.6: Satisfaction with the current accounting information system

Level of satisfaction	N=134	%
Very Satisfied	2	1.5
Reasonably Satisfied	75	55.1
Needs Improvement, but still usable	53	39.0
Dissatisfied, requires major improvement	6	4.4

Further analysis of the importance of quality factors in the Accounting Information System and its performance reflect the level of satisfaction toward the accounting system they currently have. The importance and performance of the Accounting Information System was assessed in the context of four criteria – accuracy, up to date, completeness and consistency. The result reveals (Table 5.7) that the mean score addressing the importance of the Accounting Information System quality factors ranged from a 4.11 to 4.33[23]. This shows that there is agreement that these four factors are important in ensuring the quality of Accounting Information System within the department. In looking at performance of the Accounting Information System, respondents indicated lower levels of agreement on all four criteria. The mean value ranged from 2.99 to 3.31[24] (Table 5.7) which corresponded to a 'Fair' and 'Good' level of performance. In sum, respondents indicate that this four criteria- Accuracy, Up to date, Completeness and Consistency, are important.

Table 5.7: Analysis of importance and performance

AIS quality factors	Importance (Mean)	Performance (Mean)
Accuracy	4.33	3.31
Up to date	4.11	3.00
Completeness	4.18	2.99
Consistency	4.17	3.06

Exploration of the interview data assisted in understanding the views of the respondents. For example, one interviewee indicated that he was sceptical of new systems, and were very comfortable with the current system and would need to see evidence that an alternate system would be better. However, in the current system the interviewee did recognise data presentation problems were present and argued: *'With the current system, since I am familiar with it, I could say that it is better because I*

[23] The importance of four qualities was measured by agreement through likert scale represented by 1 to 5 where 1 is strongly disagree and 5 strongly agree. In this result, mean value above 4 show strong agreement toward the importance of those four factors.
[24] Performances were measured by scale 1 to 5 which 1 represent poor performance and 5 excellent performances.

can't see any real reengineering happening right now. If we want to transfer to GFMAS, there is no evidence so far...that's my personal comment. Maybe management have a plan but have not yet accomplished it. Well, I can say that BAS and CIS are very good system, this is because it was developed back in 1987, however at that time, the machines were good, data was kept brilliantly...possibly technological advancement has let our system lag behind, but actually it's analysis was broad and good for those years perhaps better than GFMAS project. That's my personal comments. I don't know, maybe after GFMAS is fully utilised it could be better, but as for now I can't see it. They said reengineering, but most of it was adopted from the old systems, supposedly they have totally different and new...perhaps their reengineering is just embracing new tools, increased speed, more user friendly interface, that's it. And maybe because with BAS and CIS we were having problems retrieving data, the data was too detailed, some of them shouldn't be there...supposedly, reengineering dealt with this problem. Which data should be there, and which should not. Management promise this new system will be better, for example, once the key points is modified, all related data is updated. Before this, we had to update at every different level....'

This interviewee continued, reflecting on the high quality of the online payment system for suppliers and clients which he felt that a good system would reflected in the efficiency of money transfers. *'Yes, they used e-SPKB for payment, meaning that once the amount is keyed in, the payment straight away is credited to the bank account. If there is a complaint from clients...for example, where is my money, why does it take 4 days, all that should be tackled first. I'm only satisfied if we have such a system.'*

Speed and error detection were identified as issues with the current system: *'There is a small problem with our current system, it takes time to get the data...it's time consuming.'* This issue is costly to the department, *'with that decision, well...Sometimes there are deadlines that we have to follow, so they have to do overtime to complete a report for example. This problem arises because sometimes the data isn't complete, since we have many branches, so in combining those data* *sometimes accuracy problems arise'* The issue of detection of errors has also caused concern. This issue arises due to '*the difficulty the user faced in accessing the required information.'* This is a result of the presence of *'many levels of information being available and sometimes this information does not meet our requirements'*. Another interviewee was concerned that often the report required cannot be produced *'Actually, it's often that we cannot produce a report with the existing system.'*

Overall, the level of satisfaction with existing departmental systems was dependent on a number of issues including the appropriateness of the data selected from the large amount of data available, an inability to produce the report in time and issues in the ability to integrate with other systems. It was also agreed that factors such as accuracy, timeliness (up to date), completeness and consistency were important in their accounting systems. Although in their view performance of the accounting information system and the level of satisfaction of the overall system was good, there was a feeling that there was a need to ensure continuous improvement to their accounting systems.

5.5.2 Data mining usage within AIS

Survey respondents were asked whether their department were using any particular software packages to assist in analysing accounting data. Only 50% of respondents indicated that their departments did use software packages to assist in the analysis of accounting data, 22% percent responded that their department did not, and 28% did not know. Given the positions of the people surveyed it is surprising that almost 30% of the respondents were not aware of the usage of particular software for accounting data analysis. When surveyed respondents were asked whether their department utilised data mining technologies, 62% did not know about it while only 19% indicated they utilised data mining technologies. This correlated with the limited knowledge many seem to possess regarding the use of analytical software for AIS, and uncertainty about the utilisation of data mining within their department. It does support the view that the usage of data mining is minimal at this time. Table 5.8 summarizes the results.

Table 5.8: Use of analytical/data mining software

	Categories	Frequency	%
Use of analysis software	Yes, please specify	68	50.0
	No	30	22.1
	Don't know	38	27.9
Use of specific data mining technologies	Yes	25	18.8
	No	25	18.8
	Don't Know	83	62.4

An important issue is identified in terms of utilisation in Table 5.9. A comparison was made between job function and utilisation. For each job category 50% or more of respondents indicated that they did not know whether data mining technologies were in use. In accounting group for example, about seventy-eight percent (38) of them were don't know about this. In this case alone, of 49 respondents with accounting job function, 38 of them were either not aware or not familiar with data mining techniques. Looking at those respondents who indicated 'yes' to this question, 48% were auditors.

Table 5.9: Primary Job Function vs. utilisation

	Utilise data mining		
Job function	**Yes**	**No**	**Don't Know**
Accounting	5	6	38
Finance	2	3	15
Information Management	3	3	3
Auditing	12	9	19
Others	3	4	8
	25	25	83

Interviews were able to offer additional insights into the utilisation of data mining technology. Three of the interviewees indicated that they utilised data mining tools. They were involved in mining, analysing and interrogating the data in their work environment. Since all of them were involved in auditing work, they seem familiar with this kind of analysis. All were using Audit Command Language programs, called a CAATs[25] method in audit. As one interviewee said: *'We use the ACL program with the CAATs method. In CAATs there are many types of software we can use, even excel. There are 2 softwares commonly used by the auditor, IDEA and ACL, here we have used ACL since 1986.'* Another describing their work. *'Auditing is based on data provided by the accountant from the general office. We audit, interrogate, for example the voucher sampling or expenditure trend analysis. We use CAATs, through software ACL...'* One interviewee commented using an ACL:*'...all data about personal salary is kept at the accountant's general office, so if we want to analyse it we request the data from them, upon receiving the data we use data mining tools, whether data from e-spkb or from salary we just use ACL...we can search vouchers, trend analysis and various analysis, salary for instance, we can see who have overpay or no salary left..We can do all that with ACL...'*

Those respondents who had adopted data mining tools in analysis were very happy with these current tools. One interviewee discussed the Audit Command Language (ACL). *'As for now, the tool that we use is the best, but I heard there is a new one, I can't recall what it was. Anyway it's acceptable because it makes our work easier, the only problem with ACL is that you need training...'* Another explains their function in helping evaluating systems. '*That's why we do an audit, for example segregation of duties, if the system doesn't develop a very tight process, we are not able to detect its weaknesses. That is our function. If there is a loophole with the system, we will inform them. In giving proof of that loophole, we do a test. In some ways it is good for the auditee to be able to know whether is there any improvement needed for their system. We can detect a probability of a loophole or fraud...'*

The utilisation of software such as ACL in everyday work has improved the speed of work. *'.... now we have, what they called ACL you know, audit command language,*

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[25] CAAT refers to computer-assisted audit technique which implies that an auditor's use of a computer-assisted audit technique via the use of certain data analysis software. This software has the ability to extract data and normally can perform a variety of queries and other analyses on the data. Some of the features are: data queries, data stratification, sample extraction, missing sequence identification, statistical analysis and calculations (Sayana, 2003). It include a range of computerized tools and procedures used by auditors in various phases of the financial statement audit, operational and special audits (Debreceny *et al.,* 2005)

so using ACL we can analyse whether the data available is good or not, reliable or not, but prior to ACL, we used a manual system, we looked at the record, manually checked it and calculated the information and manually looked at the documents, but now we use a lot of software that helps to speed up our work.'

For some departments there is a problem implementing data mining technologies as all or some of the data is kept at other sites *'At the general audit office, we do have data mining, but here in the ministry we don't have the data, all the data are with the accounting office'.*

Interestingly 81% of respondents (Table 5.8) indicated their department did not, or that they were unaware of specific data mining technologies being used in analysis. This could reflect limited knowledge about software use within the department. For example, one interviewee indicated that the current system in use was Oracle but knew little else about it. '..*So far, we don't have any specific software for analysis data for decisions...we just use the normal pc with Microsoft (excel), no specific softwares, we do it manually, manual analysis...We don't have specific software, we combine all general data, there is no software, I'm not using it, maybe there is not available at my level, I don't know'.* Or perhaps specific software was not seen to be necessary as analysis requirements are simplistic. *'Perhaps in government there are analyses activity, but not properly managed. And then we don't have software. We have all files but without software we cant come out with analysis...'.In my opinion, data within government is rather based on historical data, meaning past events, so based on that data we present for decision making, a simple analysis. For that, excel (Microsoft Excel) is enough but I am not sure about the future.'* A common response from those who did not adopt data mining technology was: *'It's not we don't need it, it just we don't have it. We just produce reports, so I'm not sure, because when I joined here, the systems were ready, so I just use it'.* A further interviewee felt lack of knowledge may be related to their level of seniority. *'In term of the system, I do not have a chance to try, because my ranking wasn't high enough to do that, maybe at the upper level, I keep and provide the data, and then they will analysis it. I often use the*

MIS. In terms of analysis, they will need to meet different requirements and will be undertaken by various peoples...'

Six of the nine interviewees commented that their departments used no specific software for data analysis. It would appear that simplistic forms of analysis are common using spreadsheets such as excel to perform basic data analysis required by their job function or the needs of management. Interviewees indicate that even though specific software may not be used for data analysis this does not mean that data analysis is not undertaken, they may not be aware of it. However, there is recognition that analytic software is important and can be utilised to increase job performance.

In conclusion, more than 50% of the respondents either did not utilise data mining or analytical software or were not aware if any was used in their department. Half of the respondents indicated that they use software packages to assist in the analysis of accounting data. However, in terms of utilising specific data mining tools for their analysis, only nineteen percent utilised such technology. Interviews also reveal that the actual use of data mining is minimal during at this time. Notwithstanding though, it is not uncommon for departments to use a generic software such as Microsoft Excel to undertake basic data analysis suited to their job function. Thus, the utilisation rates of data mining or analytical software in government departments in Malaysia could be described as moderate. The finding also suggests that the level of awareness about data mining itself was low. This may be the result of the term 'data mining' itself is technological jargon rather than an everyday terms as the interviews reveal.

5.5.3 Factors influencing organisation's decision to employ data mining

Respondents who indicated that their departments do utilise data mining tools were asked what factors were influential in the decision to employ this technology.

The four issues identified focus on technological, organisational, human resources and external factors. Responses are summarized in Table 5.10 below. Responses to the technological issues were positive in that over 80% of respondents agreed with the issues identified. Issues such as technical support, compatibility of software and a department with an appropriate ICT infrastructure are likely to be influential in any decision to employ data mining. Over 90% of respondents indicated agreement with the organisational issues agreeing that it was important to have the support of top management and adequate financial resources to support data mining technology. Human resource issues such as adequacy of training and staff with technology skills were important. There was agreement by 83% to 92% of respondent respectively that this was an influential factor to any decision to employ data mining technologies. The influence of external issues such as changing trends in management trend in private sector and the influence of politicians not appears to be that influential in the decision to employ data mining due to a significant number of respondents adopted a neutral view on these issues. However, efforts to ensure public accountability were rated highly as a potential influence (96%).

Table 5.10: Factors influencing decision to employ data mining

Influencing Factors	Agreement (By Number of Responses)				
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Factors (Technological Issues)					
11.1 Adequate technical support from vendors	7	14	4	0	0
11.2 Compatibility of software with existing operating systems	11	10	4	0	0
11.6 Up to date ICT infrastructure	11	10	3	0	0
Factors (Organisational Issues)					
11.3 Full support from top management	16	8	1	0	0
11.10 A sufficient financial resources	13	9	2	0	0
Factors (Human resources issues)					
11.4 Effective and adequate training for staff	15	8	2	0	0
11.5 Technology savvy staff	8	13	4	0	0
Factors (External Issues)					
11.7 Changes in management trend within private sector	5	5	12	3	0
11.8 Directives from politicians	2	2	15	3	3
11.9 An attempt to ensure public accountability	13	11	1	0	0

From Table 5.10, factor 11.3 (Support from top management) and factor 11.9 (an attempt to ensure public accountability) seems to be the most influencing factor in the decision to adopt this technology with 96% agreement. Interview data showed support for this factor. In one interview, it was claimed that top management support is crucial and important in the decision to utilise data mining technology. *'In implementing technology, commitment from top management is crucial because it will involve financial commitment, officers, and training...'*

In the discussion of the importance of top management commitment, a further interview expressed the influence of the politician in the adoption of technology, *'It is easier if the minister himself/herself is keen about such technology. It will then result in quick approval for provision. There are lots of processes in implementing technology in a government environment, so support from the politician or minister would be a plus...'* Although survey results for political influence were not significant, interviews indicate that politician, or top management, have a role its play in the successful implementation of technology.

In the case of factor 11.7 reflecting on the adoption of private sector initiatives within the public sector, interviews suggest that they were not really convinced that this factor was influential in the decision to employ data mining tools. As one interviewee commented: *'The trend of private sector doesn't really have an effect on the way a government should behave…'*

For another external issue, public accountability (factor 11.9), there would appear to be an expectation that the government would become more efficient, and transparent in order to reduce public complaints and increase public accountability. One interviewee commented that the increase of awareness of information technology amongst the public has also increased the expectation toward government services, '*they know that dealing with banks for example is easy, so they expect government do the same, their expectation is quite high.'* Therefore, adoption of technology would assist in achieving this expectation, improving delivery systems and lead to a more accountable government. By comparing the services offered by the private sector (i.e. banks), one interviewee contemplated his views '*For example, banking transaction are reasonably quick. We in government have to follow the transitions of* *technology. Therefore now, citizen can do their transactions using credit cards through e-procurement and e-payment, pay their taxes'.*

Interviewees also supported the human resources issues as influential in the decision to employ data mining technologies. As one interviewee argued not only do staff need to understand financial data, but also develop Information Technology (IT) skills in the management of financial data. This interviewee's department has already made a proactive step by requesting IT personnel for each section within the department . '*We're applying for officers with Information Technology (IT) background located in every section of our department.'* A number of interviewees indicated that their departments utilise software in undertaking data mining activities, commonly Audit Command Language (ACL). Interviewees indicate that it is easy to learn and use. There are many workshops conducted by the ministry for different levels of user for programs and applications. As one interview commented, *'workshops for using ACL software to the extent of interrogation were conducted regularly'*

Interviewees indicated that technological and organisational issues were important factors in their decision to employ data mining. Support from the vendor at the initial stages of implementation was identified to be very important. Ease of use and friendly interfaces in software, financial support for the project, a working culture supportive of change were all important factors. One interviewee in commenting on work culture said: '*The culture of the work environment has to be propagated, top management put forward initiatives. Then slowly we change. We are now in the process of becoming accustomed to the new culture. The awareness of our staff is also good. We have one to one ratio of PCs to staff.'*

Apart from these factors one additional factor emerged from the interviews. It relates to change in the public sector itself, a policy by the government to move toward a paperless office, leading to greater use of computers and a need for increasing data storage with the department. In this sense data mining tools are seen as increasingly important to enhance the ability to explore the data and generate information to support better decision making.

Many of the Departments that indicated they were utilising data mining had adopted Audit Command Language (ACL). Data mining activities includes the interrogation of data to enhance internal control and.to look for potential fraud One influence in the decision to utilise such technology is for tasks requiring respondents to investigate, interrogate and undertake the analysis of data regularly. The factors identified above are important influences likely to result in better utilisation of data mining or any new technology within the public sector. Additionally, based on interviewees it would seem that a political factor (external issue) may also be important.

5.5.4 Reasons for not utilising data mining

Respondents who indicated that their departments were not adopting data mining technology indicated reasons that could be classified as technological, organisational, or human resource issues. The responses are shown in Table 5.11 below. In terms of technological reasons many respondents indicated that the adoption of technology was too complex and time consuming (36%), difficult to find the appropriate software (56%) and they were satisfied with the current system in place (48%).

Organisational reasons identified for not adopting data mining technology included a lack of top management support (44%), a lack of policy development (40%) issues that were more important to resolve (36%) and the cost to implement new technology (68%).

Lack of expertise (56%) and a lack of awareness (60%) of data mining technologies were identified as major reasons for not adopting the technology.

Table 5.11: Reasons for not utilising data mining

Reasons	Agreement (By Number of Responses)				
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Technological Reasons					
12.1 Satisfied with current analysis method	0	12	10	2	1
12.6 Difficult to select appropriate software	1	13	10	1	0
12. 7 Too complex and time consuming	2	7	11	4	1
Organisational Reasons					
12.4 Costly to implement new technology	2	15	6	2	0
12.5 Lack of top management support	2	9	10	4	0
12.8 Lack of management policies	2	8	10	5	0
12.9 Having more pressing problems	3	6	12	2	2
Human Resources Reasons					
12.2 Lack of expertise to implement data mining	4	10	9	2	0
12.3 Lack of awareness about data mining	6	9	8	2	0

There would appear to be major challenges in technological, organisational and human resource issues for non-adopters to move forward to adopt data mining technology. Interview data supports this result that technological, organisational and human resource issues are an important challenge faced by the public sector in employing technology. Having a good and viable technological infrastructure which is properly set up could reduce problems. As one interviewee commented: '*our infrastructure development lagged behind in supporting our system, for example, telephone lines, local area network (LAN) is very fast but hangs, the line drops out. Actually these sorts of problems should be addressed first. Then we could have a global system to represent government's data'*. The implementation of technology has to come with proper policies of usage, working procedures, training phases and better planning. One interviewee commented: '*For example one department has decided to implement a technology but before it reaches us, sometimes that technology has already become obsolete. That's where I could see some obvious drawbacks. We can still carry on, but the thing is, when it is time to implement such technology it seems that we are 2-3 years behind. If there is an advance in technology we can't implement that, decision makers in government are wary, and there are too many steps that we have to look.'* This suggests the importance of having good management policies which will then assist in resolving new developments and managerial problems quickly. At present bureaucracy may be restricting the implementation of good decision, or at least delaying them.

Finance was identified as a reason for not utilising data mining by one interviewee. The interviewee argued that the government must make financial resources available '*In my opinion, there is a need for the government to catch up with the technology, but we have to follow policy, I mean the budget...'* Although another interviewee discounted this reason arguing that there was always a provision and budget for the information technology development, giving an example of the development budget provided for (8th Malaysia Plan)[26] of RMK8. This was argued to be a substantial amount provided for the development of systems.

The human resource issues such as lack of expertise, lack of awareness found to be significant reasons appear to be related to the attitudes of the public servants toward technology as perceived by interviewees. While workshops are readily available for example, one interviewee stressed that the attitude of staff is very important in whatever training or workshops are conducted by the departments '*attitude, I think that one is very important, to me whatever system we have, if our attitude is not right, you know software is just a software, hardware is just a hardware, it cant run without the human touch. Somebody has to push it...'* One respondent suggested that culture in the Malaysian environment, especially Malays, result in a reluctance to change and result in lags in the introduction of new technology. *'The infrastructure has to enable a full support, if not the users will become frustrated and lose their interest. This often occurs in our Malaysian culture and environment especially with Malays who least use IT or any system which could help them because they are reluctant to change toward technology.'*

[26] The Eight Malaysia Plan, covering the period 2001- 2005, is the first phase in the implementation of the Third Outline Perspective Plan (OPP3), 2001-2010. The OPP3, which embodies the National Vision Policy (NVP), will chart the development of the nation in the first decade of the 21st century. Sources: http://unpan1.un.org/intradoc/groups/public/documents/APCITY/UNPAN017502.pdf

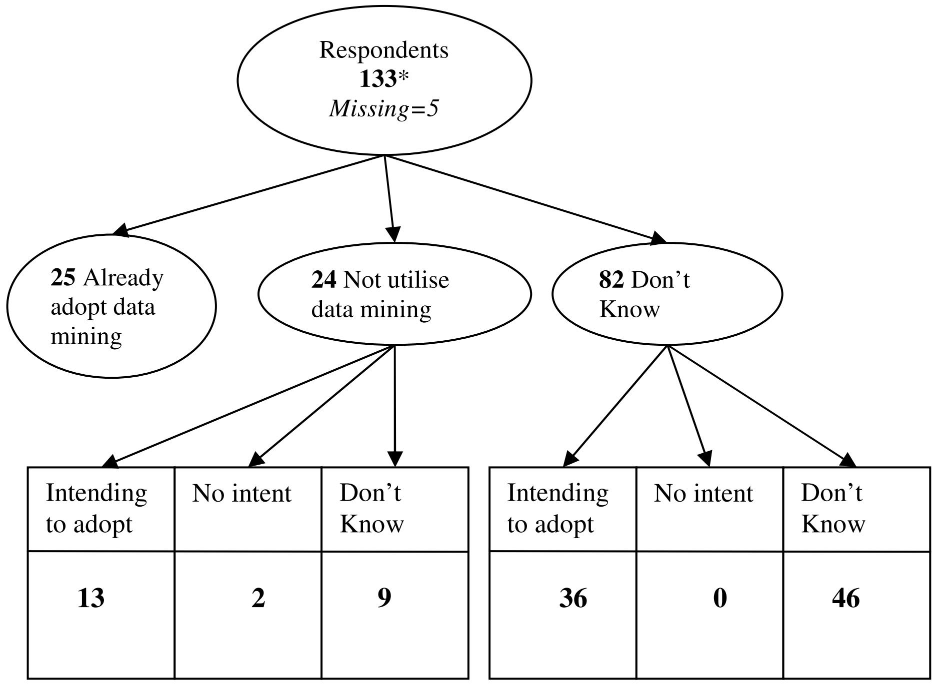
In another interview, discussing the attitude of his subordinates toward technology, he claimed that '*sometimes people seem to be reluctant, it is not that they are saying it is not good, perhaps they just don't want the additional burden of new workload, new things that must be learnt from the beginning...sometimes they don't see the benefits of that. So we have to do road shows, workshops, presentation, it can't be achieved overnight. So we have to do the marketing, so that they will see more clearly.*'

In sum the reasons identified above are the major obstacle and challenge in utilisation of data mining or any new technology within the public sector. Those reasons fall under the three issues of technological, organisational and human resources.

5.5.5 Intention to adopt

In Figure 5.1 below respondents are classified by the intention of their departments to adopt data mining technologies. Of the 133 respondents 82 did not know whether data mining technologies were in use, and 24 indicated that their departments did not utilise data mining technologies. Of the 82 respondents who did not know 36 respondents were aware that the intention of the department was to adopt data mining technologies, while 13 of the 23 respondents who indicated that their departments did not utilise data mining technologies do intent to adopt it. The results show both promise and concern, promise in that many departments plan to adopt data mining but concern that many managers do not know what the department currently utilises in this regard nor what the intent of the department is.

Figure 5.1: Classification of respondents by intention to adopt data mining



Note:* There were 138 respondents, however there are 5 not answer the question

The interviews assist in understanding part of the promise identified. One interviewee noted: *'As I said before, for those of us in the government, there is little data mining undertaking. Maybe in the future, our department will use data mining for decision making.'* Another indicated the department had adopted a new system called GFMAS which would allow the department to implement data mining strategies in the future. This respondent indicated a belief that data mining technology would assist in undertaking the job role. *'In GFMAS, there is a component which moves toward data mining, perhaps in terms of implementation, the only thing is to implement it, so for me training from the developer is important...'* However this interviewee was not so sure when full implementation of data mining might take place *'I'm not sure when it can be ready, it is because in our annual report we do have analyses for every year, on financial analysis, all the ratios, we did all that every year manually from available data.'* Therefore, he agreed that data mining could help reduce the time consumed to analyse data in the preparation of annual financial reports.

Further interviews show an optimistic opinion about the potential use of data mining within public sector. As one interviewee recalled:*'If we focus toward the long term, that technology is required because in government, we do need analysis beyond the spending aspect only. At the moment we concentrate our focus on how to spend, you get the budget and spend, then request more, that's it. But if we focus more broadly the government actually should consider it revenue, we are heading toward that. So, I think that data mining is definitely important, because it can impact on our decision, if the government wants to be very accurate and efficient. We need to change our focus, not only focus on getting the budget and spending.'*

Respondents, particularly at the interview suggest that the use of data mining technology within public sector will increase in the near future. Interviewees had a positive attitude and were ready to learn, accept and use such technology in their workplace. Across both surveyed respondents and interviewees the study found that there was strong indication that their department will employ data mining technologies in the future. Forty-six percent of respondents (49 of 106[27]) indicated their departments' intention to adopt such technology compared to 10 per cent of respondents (11 of 106) who indicated that their departments had no intention to adopt data mining techniques. The concerns identified reflected to the level of awareness and knowledge of data mining technologies within working environment. It appears that the majority of respondents were not aware of data mining, or even of the analytical software used in their current system.

5.6 Data Analysis-Research Question One

5.6.1 Is the concept of data mining accepted?

This study sought to identify whether respondents within the public sector understood the concept of data mining, and whether they believed that data mining techniques were important to the operation of their department's information system especially the accounting information system. The research question posed was:

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[27] 106 (number of current adopters, 25 was excluded).

Research Question 1: *Do management and staff in the Malaysian public sector have an understanding of the concept of data mining and accept the relevance of the techniques of data mining in day-to-day accounting activities?*

The response to this question will be discussed firstly in terms of their awareness of data mining techniques and secondly, in terms of their readiness to accept and adopt data mining technology.

a) Awareness of and knowledge of data mining techniques

Awareness of data mining was quite limited (see Table 5.12). Only fourteen percent (19 respondents) indicated that the term of data mining were used in their organisation while over fifty percent (74 respondents) were not know that the term had even been used within their departments, and over eighty percents of respondents (103) were not sure whether or not an alternative term had been used to describe the similar meaning of data mining. There are few lists however, which is perceived and used as an alternative to data mining provided by respondent. They include: *Analysis, Business Warehouse (BW), Computer Assisted Audit Tools (CAATs), Data Analysis, Data Interrogation, Data into informed information, Management Information Systems(MIS), Performance report, and Statistic*.

The level of knowledge about data mining techniques identified by respondents is also shown in Table 5.12 below. About seven percent of the respondents (10) had a good knowledge, almost forty percent of the respondents (54) with an average knowledge, thirty-five percent of the respondents (48) indicated that they had little knowledge and eighteen percent of the respondents (25) has no knowledge at all. The table also shows that none of the respondents had a rich knowledge in data mining.

Table 5.12: Frequency on awareness of and knowledge of data mining

	Frequency	Percent
Use of data mining term		
1. Yes	19	14.1
2. No	42	31.1
3. Don't Know	74	54.8
Other terms that means data mining		
1. Yes	12	9.6
2. No	10	8.0
3. Not Sure	103	82.4
Knowledge about data mining		
1. No knowledge	25	18.2
2. Little knowledge	48	35.0
3. Average knowledge	54	39.4
4. Good knowledge	10	7.3
5. Rich knowledge	0	0

From the surveyed respondents more than eighty percent of respondent (116) indicated the term data mining had either not been used or they had no knowledge about use of such term. In the interview, concerns about the awareness of and knowledge of data mining term also emerged. One interviewee commented that no such term had been used in her department. Explaining further, *'Before this, we used mainframe. There is no data mining. There's none. We just produce normal reports. So with new system we do have data warehouse and there will be data analysis activities in it. We do have data analysis activities but not using any specific tools for it'.* Another interviewee also revealed that she has never heard the term and assumed that data mining was similar to the Knowledge Management (KM) concept. In another interview however, the interviewee indicated that she has heard of the term but was not sure what data mining was '*I've heard this term but do not know what it is exactly, what the meaning of it, what can I imaging is tin mining.... if you were not involve in it you tend to not bother about it....'* Furthermore, she also had a perception that data mining might involve only the private sector rather than be applicable to the public sector as she argued the sectors have a different perspective. The term has recently received attention in the development of GFMAS '*but how to use it I don't know...they said drill down or whatever...we did discuss it the other day…we discussed last year, I've heard about this but never use it, I heard it can do many things and very flexible...can do so many analysis, yet we never use it here.'*.

In another interviews, the interviewee also indicated she has heard the term in her study but had limited knowledge about it. She suggested that awareness activities should be conducted sooner rather than later. *'If we focus on the future, data mining is actually should be used from now, an awareness should be instill from now because this thing cant be done in a split second, exposure to all staff has to be done now so then the transition will smoothly move.'*

Only fourteen percent had used the term data mining and about ten percent used alternative terms. Lower rates of response to this question may reflect the level of awareness and also the terminology used itself. There does appear to be mixed understanding about the term data mining. This is because the terminology itself relates to the computer jargon rather than in broadly use. As one interviewee commented '*the terminology is computer jargon and here that jargon was not broadly used. However, we have use this software quite some time but we called it as CAATs, so terms that we use is CAATs which I believed also data mining...for instance, I show you here is the guidelines to the system and software application on how to use it, since it is fully automation transaction, from preparing vouchers to auditing, there are elements of control there, fraud elements and others which I consider it as data mining as well. It actually depends on how creative we are to do the analysis with this software.'*

In another interview, the interviewee thought data mining was part of the Management Information Systems (MIS) she used. The MIS was adopted in producing financial reports, management trial balance, contractor analysis, supplier analysis according to projects and other sorts of reports. She accepted that the MIS does not have forecasting capability as data mining would. *'The best I know is MIS, It evaluates and analyse current and past data. It doesn't go beyond that such as forecasting though...'*

Overall, the term of data mining was not very familiar among interviewees and surveyed respondents. They might have heard the term but were not well aware of its use. A number have used different terminology such as CAATs. Surveyed responses show forty-six percent of respondents (64) indicate they have average or above knowledge about data mining, there was a lower percentage in terms of awareness about the use of that term or other related terms. Interview data showed similar evidence that the level of awareness of data mining among public sector staff was quite low. Interviews also suggests that job scope play it roles in the awareness of the staff as one interviewee recalled: '*Staff are aware of it, but in order to fully utilise the software, it depends on your job scope, so if your work doesn't involve these things, then you don't use it. However, with changes in environment, for example increase in automation, meaning that all steps are fully automated and you don't have a choice, you have to use it. It does depend on individual cases, when related to them, they will use it...in general staff are aware about it, some of them even can use it...'* Most interviewees believed that exposure through awareness raising programs would be beneficial.

b) Data Mining Readiness

Data mining readiness has been judged by four components, optimism, innovativeness, and perception of easy to use and usefulness.

The responses are shown in Table 5.13 below. Responses to the optimism component were positive in that over seventy-three percent up to eighty-seven percent of respondents agreed with those statements. Many respondents indicated that the technology will give them a greater control over their daily work (85%), application of newest technology would be convenient to use (77%), they prefer to use most advanced technology available to them (73%), increase their work and occupation efficiencies (86%) and also agreed that it is a good idea to have data mining technology in analysing the data as an additional method they currently use (86%).

The descriptive statistics shown in Table 5.13 all indicate that all respondents agree with these statements as representing their optimism toward data mining readiness. The mean was greater than 3, the mode and median 4 for each statement equating to agreement. All t-tests were positive and significant as summarized in the table. Positive and significant results were found for all statements representing optimism. Statement 8.1 indicating that the technology gives a greater control over daily work shown a positive and significant, ($t(132)=19.478$, $p<.001$). Similar positive and significant result were also yielded for statements such as products and services that use the newest technologies are much more convenient to use (statement 8.2, $t(132)=15.265$, $p<.001$), I prefer to use the most advanced technology available (statement 8.3, $t(132)=14.735$, $p<.001$), Technology makes me more efficient in my occupation (statement 8.4, $t(131)=20.430$, $p<.001$) and I think it would be very good to use data mining technology for analysing accounting data in addition to current methods (statement 8.10, $t(132)=18.831$, $p<.001$).

In the case of innovativeness, responses also show high percentage of agreement on those statements (statement 8.5, 8.6 and 8.7). As shown in the Table 5.13, majority of the respondents indicated that they always keep themselves up to date with the latest technological development in their areas of interest (66%), having a fewer problems making the technology working for them (66%) and always open and keen to learn a new and different technology available to them (91%). Descriptive statistics indicated that all statement representing innovativeness are scored a mean greater than 3, with mode and median for these statement equal to 4. T-test on those three statements shown a positive and significant result, ($t(131)=12.378$, $p<.001$, $t(132)=11.070$, $p<.001$ and $t(132)=21.850$, $p<.001$) for statements 8.5, statement 8.6 and statement 8.7 respectively.

Table 5.13: Readiness toward data mining technology

Statements	Agreement (By Number of Responses)					Descriptive Statistics			t-test[28] (two-tailed/test value=3)	
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mode	Median	Mean	T Value	Sig.
Optimism										
8.1 Technology gives me greater control over my daily work	35	78	19	1	0	4.00	4.00	4.1053	19.478	.000
8.2 Products and services that use the newest technologies are much more convenient to use	19	84	26	4	0	4.00	4.00	3.8872	15.265	.000
8.3 I prefer to use the most advanced technology available	32	65	34	2	0	4.00	4.00	3.9549	14.735	.000
8.4 Technology makes me more efficient in my occupation	39	76	16	1	0	4.00	4.00	4.1591	20.430	.000
8.10 I think it would be very good to use data mining technology for analysing accounting data in addition to current methods	36	79	15	3	0	4.00	4.00	4.1128	18.831	.000
Innovativeness										
8.5 I keep up with the latest technological developments in my areas of interest	20	68	40	4		4.00	4.00	3.7879	12.378	.000
8.6 I find myself having fewer problems than other people in making technology work for me	13	76	37	6	1	4.00	4.00	3.7068	11.070	.000
8.7 I am always open to learn about new and different technologies	44	77	10	2	0	4.00	4.00	4.2256	21.850	.000
Easy to Use										
8.8 It is easy to learn how to use technology	30	69	29	5	0	4.00	4.00	3.9323	13.952	.000
Usefulness										
8.9 Overall, I find the technology useful for any task I need to accomplish	36	78	18	1	0	4.00	4.00	4.1203	19.823	.000

[28] One-Sample t-Test was used with 3 as the 'test value' which represents a midpoint of agreement. Value above 3 suggests that respondents generally agreed to that statements toward data mining readiness

Many of the respondents also indicated that they perceived the technology as easy to use when they agreed that the technology is easy to learn on how to use it (74%). T-test on this statement (statement 8.8) produced a positive and significant result, $t(132)=13.852$, $p<.001$. The majority of the respondents were also agreed that they found the technology is useful for any task they needed to accomplish (86%). This single statement representing the usefulness issue, resulting a positive and significant t-test, $t(132)=19.823$, $p<.001$. The results are suggesting that public servants are receptive toward data mining technology. They have a positive view of technology, a tendency to be a technology pioneer, perceived the technology to be useful and easy to use. All four components of readiness suggested in the study was found to be a positive and significant indicating the readiness of management and staff in the public sector toward data mining technology.

Interview data supported readiness toward data mining technology as they were very optimistic, innovative and have a perception on easiness and usefulness of such technology in their working environment especially. One interviewee optimistically claimed that all the staff and management in the public sector should be involved in the technology. As she recalled *'...each of us has to be involved….it is because our government are moving toward technology, for me, what is the reason for staying with manual system where we know that it is time consuming and troublesome...'* Another interviewee was also optimistic to the need for software such as data mining '*because it certainly can help us, if not we are struggle to find those information when we needed them. Sometimes we have to do some overtime work to finish the job, if we have a good software it will help us in doing our job'*.

Innovativeness characteristics were identified in the interviews in which interviewees indicated positive attitudes toward technology and openness to learn new and different technologies such as data mining. As one interview claimed that skills have to be sharpened as progress is made: *'...I mean personally if you ask me personally, in fact I tell you prior to joining this office, I have very little knowledge in computer, using software all that, but because of the need, we have no choice otherwise you have no place in this environment, so we need to learn even though sometime we* *don't like it, you know..'* Change in systems had resulted in departments conducting compulsory workshops and training compulsory '..*You must have the skills that relate to your level....'*

For some interviewees, obtaining a professional certificate in technology and undertaking formal education in technology should be seen as normal practice. One interview reveals that *'Apart from having an accounting background, I also have certificate in ICT, in MIS, I completed a one year course at Universiti Teknologi Mara (UiTM).* A willingness to learn was typical for interviewees, *'we're willing to learn, we're willing to adjust and learn'*. One interviewee commented that she positively accepts the transition of BAS system to GFMAS and the ability to use computer technology is necessary to be an accountant nowadays. She also felt more confident in her work when using computer technology.

Interviews also showed a strong perception relating to ease of use and usefulness of data mining technology. *'If you receive training and at the same time have a positive attitude, those who are very good with computers, after training they can do the task straight away'*. Another interviewee also agreed by saying that minimum training would be enough '*a minimum training, we conducted here, in-house training, overall the software is easy to use.'* In the case of the usefulness of the technology, interviewees reflected a positive attitude as one interviewee commented that *'So with this data mining it really makes our work very easy, and we can get the results we want almost immediately, I cannot imagine if we had to do this manually…'*

Respondents were positive toward accepting technology. They believed that the implementation of new technology is a must and needs to be supported. Any government's project toward implementing new technology should come with proper programs to ensure the attitude of workers supports implementation, workflow is appropriate, and manuals and appropriate infrastructure is established. It is also important that all staff and management see technology as a tool which can help them in their workplace.

5.7 Data analysis-Research Question Two

The second research question considers the impact on decision making of the utilisation of data mining technology in the accounting information system. The question posed was:

Research Question 2*: In the operation of the accounting information system how would, or does data mining impact on the effectiveness of public sector decision making in Malaysia?*

Accounting information systems data is being used in decision making. Table 5.14 shows that twenty-five percent of respondents (30) used accounting information data fairly often in decision making, while twenty-six percent (42) often use accounting information data and seven percent (14) of respondents frequently use data from AIS for decision making. It represents more than fifty percent of respondent who regularly use data from the Accounting Information System (AIS) in decision making.

Table 5.14: Frequency use of accounting data from AIS in decision making

Frequency of use	n	%
Seldom	29	23.0
Occasionally	20	19.3
Fairly often	30	25.2
Often	42	25.9
Very often	14	6.7

Data from the AIS is important in the decision making process. Any application or utilisation of technology such data mining within the AIS offers support to the decision making process. Respondents were asked what they thought the impact of data mining would be on the performance of AIS and the decision making process (Table 5.15).

Table 5.15: Perceived impact of data mining

Statements	Agreement (By Number of Response)					Descriptive Statistics			t-tests[29] (two-tailed/test value=3)	
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree	Mode	Median	Mean	T Value	Sig.
Impact on AIS										
14.1 Lower transaction cost	15	68	49	3	0	4.00	4.0000	3.7037	11.817	.000
14.2 Increase the quality of information derived from AIS	35	81	18	1	0	4.00	4.0000	4.1111	20.090	.000
14.3 Increase AIS performance	27	85	20	3	0	4.00	4.0000	4.0074	17.641	.000
14.4 Improve the quality of transaction data	27	80	26	2	0	4.00	4.0000	3.9778	16.847	.000
14.5 Reduce cycle time of the department	21	84	26	4	0	4.00	4.0000	3.9037	15.468	.000
Impact on Decision Making										
14.6 Meet the information needs for the decision making	33	78	22	2	0	4.00	4.0000	4.0519	17.876	.000
14.7 Provides decision support in decision making	34	76	24	1	0	4.00	4.0000	4.0593	18.163	.000
14.8 Contributes to the speed of decision making	29	80	26	0	0	4.00	4.0000	4.0222	18.550	.000

[29] One-Sample t-Test was used with 3 as the 'test value' which represents a midpoint of agreement. Value above 3 suggests that respondents generally believed, perceived this as an impact of utilising data mining technology within accounting information system in the department.

In the case of the impact of data mining on the AIS sixty-one percent of respondents (83) agreed that data mining would lower transaction costs, eighty-six percent of respondents (116) agreed that data mining would increase the quality of information derived from AIS, eighty-three percent of respondents (112) agreed it would increase overall Accounting Information System (AIS) performance, seventy-nine percent of respondents (107) agreed it would improve the quality of transaction, and seventy-eight percent of respondents (105) agreed it would reduce cycle time of their organisation. The majority of respondents were agreed that data mining would have a positive impact on their accounting information systems.

Descriptive statistics (Table 5.15) indicated that the mean values for all eight statements or impacts were greater than 3, with mode and median equal to 4. Respondents were found to have a positive and significant agreement regarding the anticipated impact data mining would on the Accounting Information System (AIS). Data mining was perceived to have a positive impact on the Accounting Information System (AIS) by lowering the cost of transactions (statement 14.1, $t(134)=11.817$, $p<.001$), increasing and improving the quality of information available from the Accounting Information System (AIS) (statement 14.2, $t(134)=20.090$, $p<.001$) and improvement in the quality of transaction data (statement 14.4, $t(134)=16.847$, $p<.001$), reducing the cycle time of the department (statement 14.5, $t(134)=15.468$, $p<.001$) and increasing the overall performance of the Accounting Information System (AIS) (statement 14.3, $t(134)=17.641$, $p<.001$). Positive and significant results on all statements reflecting the impact of data mining on AIS shows a strong perception among the respondent toward the benefits and goodness of having such technology within their accounting systems.

In the case of the impact on decision making eighty percent of respondents agreed that the utilisation of data mining would fulfil the need of user for information required (111), provide support to decision making (110), and increase the speed of the decision making process (109). Descriptive statistics indicated the mean values were greater than 4, with mode and median equal to 4. The mean value greater than four indicates a strong agreement toward each of those statements among respondents. T-test on those three statements yielded a positive and significant result, $t(134)=17.876$, $p<.001$, $t(134)=18.163$, $p<.001$ and $t(134)=18.550$, $p<.001$ for statement 14.6, statement 14.7 and statement 14.8 respectively. These results indicate that data mining provides benefits by making available information to meet the needs for decision making by users (statement 14.6), providing support to the decision making process (statement 14.7) and increase the speed of the decision making processes (statement 14.8).

From the interviews, similar perception can be identified through discussion about performance of the accounting system and potential use of data mining in it. One interviewee responding to the ability of data mining software to increasing the capability of the accounting system commented '*increase the ability of the system…yes, because with this, data are properly kept, records are properly kept and when they are properly, it means they are accurate, timely, so definitely will enhance the accounting record, the whole system in the government'*. He further commented that a timely and accurate analysis would be able to achieve through data mining. '*We can give timely, and accurate analyses in solving problems faced by the ministry, for example revenue, how much revenue they collected, how much government collect and analyse the reason why this thing happen and in term of the possibility of fraud and all this'*. It would further help to enhance the level of financial management in the government.

Another interviewee also expressed agreement about the impact data mining would have on the AIS. *'Yes definitely, with data mining we will be able to know its performance, what the problems, volumes, why sometimes it's late. We can measure how many days they take processing any tasks, we even can trace back any steps been taken...its time frame, if there is any overdue we will know. All this while, it is hard to know all this'*. One interviewee indicated that the use of data mining would reduce the probability of missing out some important facts: '*So if we have report with analysis of percentage, charts and others, we could see more...that's good.'*

A majority of surveyed respondents agreed that data mining would have an impact on decision making, interviewees supported this perception. Interviewees argued that additional software such as data mining tools in their work would help them to identify the information required in whatever decision was being made. One interviewee indicated that: '*By using ACL, we can make a decision more quickly, and in terms of operation as well'* and will increase his capability in decision making process. Another commented: '*I believe when many of us have used it, by that time our decision will be useful. It definitely assists our decision. With these guidelines, we can make a conclusion to the system we audit, their weaknesses, the risk whether it is low or high...'* He further suggested that such technology should be utilised by every department '*I think this type of software should be used in every department even non-accounting departments, when organisation make a decision, any steps taken supposedly based on fact, these facts came from analysis, so in doing this analysis...we have the information, the data, it's unfortunate we do not use the data. In terms of operational, it is true that the first phase we create data. For public sector, that phase we have achieved, the next level is to utilise those data, so supposedly we are now entering to an era of utilising the data....'* The reason for suggesting this is because he believed that most of the decision making in the public sector did not use fact for analysis. *'Facts actually relying on data, perhaps one day...we tried in our department, we introduce the methods, in some ways introducing this software and the method of work, so we are making it as a customs, so hopefully it will spread to other department and ministries...'*.

Another interviewee agrees about the importance of data mining in the process of decision making '*I am very positive about it because it certainly assist us in making a right decision, with that data we can make a decision...it is true our decision is depend on us but with good data it will even better.'*.

Data mining could have a significant impact on the AIS and the decision making process. Respondents believed that data mining technologies will help in getting better information, and more factual data for use in the decision making processes. The use of data mining technology in the accounting information system would have an impact on the performance of the departments accounting system and would also improve the effectiveness of government decision making processes. Utilisation of data mining, will improve overall performance of AIS by lowering down transaction costs, increasing the quality of information and reducing cycle time of the department. It supports the recommendation made by various researchers (Debreceny *et al.,* 1999, Weber, 2002, Burns, 2003) that data mining would ensure a production of a good financial statement, increasing the accuracy and reliability of accounting information and effectively provide information for decision makers and assurance of internal control.

The utilisation of data mining was also believed to improve decision making process within the public sector by supporting the need for information, speeding up an informed decision process and providing a support system to the whole decisions process.

5.8 Data analysis-Research Question Three

The third research question examined the importance of data mining techniques as a criterion to assess the performance of an Accounting Information System in the government sector. The question posed was:

Research question 3*: Is the ability to utilise data mining techniques one of the important criteria in assessing the performance of Accounting Information System in the Malaysian public sector?*

This research question is intended to investigate whether data mining utilisation is a major issue or important criteria in assessing the performance of AIS.

Apart from four qualities of AIS[30], other important factors considered in the process of evaluating the performance of AIS were suggested which also include statements which relating to the ability to utilise data mining. The first part of the questionnaire

[30] Four quality factors of AIS performance: accuracy, up to date, completeness and consistency.

(question 5, see Appendix 1.2) asked respondents to indicate their agreement on the importance of factors reflected in the evaluation of the performance of the Accounting Information System (AIS). Table 5.16 summarizes the responses. Nine-five percent of the respondent (130) agreed that ease of use of the system (factor 5.1) was an important factor in assessing the performance of the systems (this factor ranked number 1). Ability to automatically validate the data (93%, rank 2), having an adequate and sufficient documentation (86%, rank 4), that was easy to modify and upgrade (79%, rank 5), and the ability to implement new data analysis tools (such as data mining) (77%, rank 6) having an effective data management approach via a centralised database and data warehouse (88%, rank 3) were also identified to be important factors in the process of evaluating the performance of AIS.

Table 5.16: Important factors for evaluating the performance of AIS

Factors	Agreement(By Number of Responses), % and ranking			
	Strongly Agree	Agree	Percentage agree %	Rank[31] of most important factor
5.1 The systems are easy to use	69	61	94.9	1
5.2 The systems are able to automatically validate the data	74	54	93.4	2
5.3 The systems have an adequate and sufficient documentation for employees to follow	80	38	86.1	4
5.4 The system are easy to modify and upgrade	56	52	79.4	5
5.5 The systems implement new data analysis tools (such as data mining)	48	56	76.5	6
5.6 The systems have an effective data management approach such as, centralised database and data warehouses	64	57	88.3	3

In responding to this third research question, an ability to utilise data mining within the Accounting Information System (AIS) was represented by statement 5.5 (The systems implement new data analysis tools) and statement 5.6 (The systems have an effective data management approach such as centralised database and data warehouses). Statement 5.5 specifically referred to the actual implementation of data mining technologies while statement 5.6 referred to the existence of a centralised database to enable data mining to be efficiently undertaken within the system. Descriptive statistics (Table 5.17) showed that the average response to those two

[31] Ranking was base on the summated percentage of agreement toward each factor. It indicated that the higher the ranking is the more important the factor is, in evaluating the performance of AIS.

factors was greater than 3 with mode and median equal to 4 in case of statement 5.5 while mode of 5 and median of 4 for statement 5.6. T-Tests also indicated significant results for both statements (($p(135)=14.417$, <.0001 and $p(136)=19.629$, <.0001) respectively which indicate respondent agrees that the ability to implement new data analysis tools and having an effective data management via centralise data warehouse, are importance in the process of evaluation of their Accounting Information Systems within government sector.

Table 5.17: Descriptive statistics: Factors representing the ability to utilise Data Mining

Factor	Descriptive Statistics			t-tests[32] (two-tailed/test value=3)	
	Mode	Median	Mean	T value	Sig
5.5 The systems implement new data analysis tools (such as data mining)	4.00	4.000	4.0662	14.417	.000
5.6 The systems have an effective data management approach such as, centralised database and data warehouses	5.00	4.000	4.3139	19.626	.000

Interviews also indicated the importance of data mining utilisation in that it enabled the department to access reliable and up to date data. Interviewees commented that accurate data, fast, timely, current and data accessible online were some of the vital factors in assessing the performance of the AIS. The ability to utilise data mining for example in doing forecasting *'makes our work a lot easier'*. However, across the interview data, interviewees were more likely to discuss the importance of basic requirements such as the ability to generate reports on a periodical basis, data control, easy of access, flexible reports, integrated with other systems, real time data, security features, strong internal control and systems with audit trail. The system itself needed to possess user friendly interfaces, be easy to understand, easy to use and offer completeness for reporting. *'...as a user, I like the software to be user friendly, the data that we have is current, and in terms of reporting, it has various functions upon request base on our requirement. That's it that we want.'* A basic requirement

[32] One-Sample T-Test was used with 3 as the 'test value' which represents a midpoint of agreement. Value above 3 suggests that respondents generally agreed that the factor was important in evaluating the performance of AIS.

was technology that exhibited fewer problems within the working environment. '*A good accounting system is actually one which doesn't have much problems...what ever you key in, it will correctly record, accurately, quickly and give an impact to satisfied users. For example, in terms of collections, when they pay we can retrieve all the data, all the receipts, we can give a prompt feedback to the tax payer as fast as possible. The other thing is, we record as correct as what we collected. That's for the incomes. For the payment, we only need to key in once and the payment goes straight to payee's bank without hassle, so they can get the money quicker and also with a very good maintenance.'*

Another important criteria or factor was internal control. As one interviewee commented: *'A good system... internal control is very important, in designing it, all the possible loophole were considered. Possibilities of errors, misconduct or fraud is important. We don't want any unsystematically error to the system. Normally, problems arrive when the developer just developed it just for the sake of getting it done. For example, if the objective was to make a payment, so as long as the system could pay then it is ok. However, in terms of payments, there must be a control mechanism, whether the payment is genuine, is the approval come from the right person, is there any supporting documents, any allocation for that payment, all that has to be considered.'*

Typically a good accounting system is one perceived to be useful, exhibits fewer problems, easiness (easy to use, to understand, user-friendly), reports which are current, timely, accurate and enable good internal control. The responses show that the ability to utilise data mining was a significant factor quantitatively and the interviews were able to draw out the issues. Therefore it can be concluded that the ability to utilise data mining techniques is one of the important criteria in assessing the performance of Accounting Information System in the public sector.

5.9 Data analysis-Research Question Four

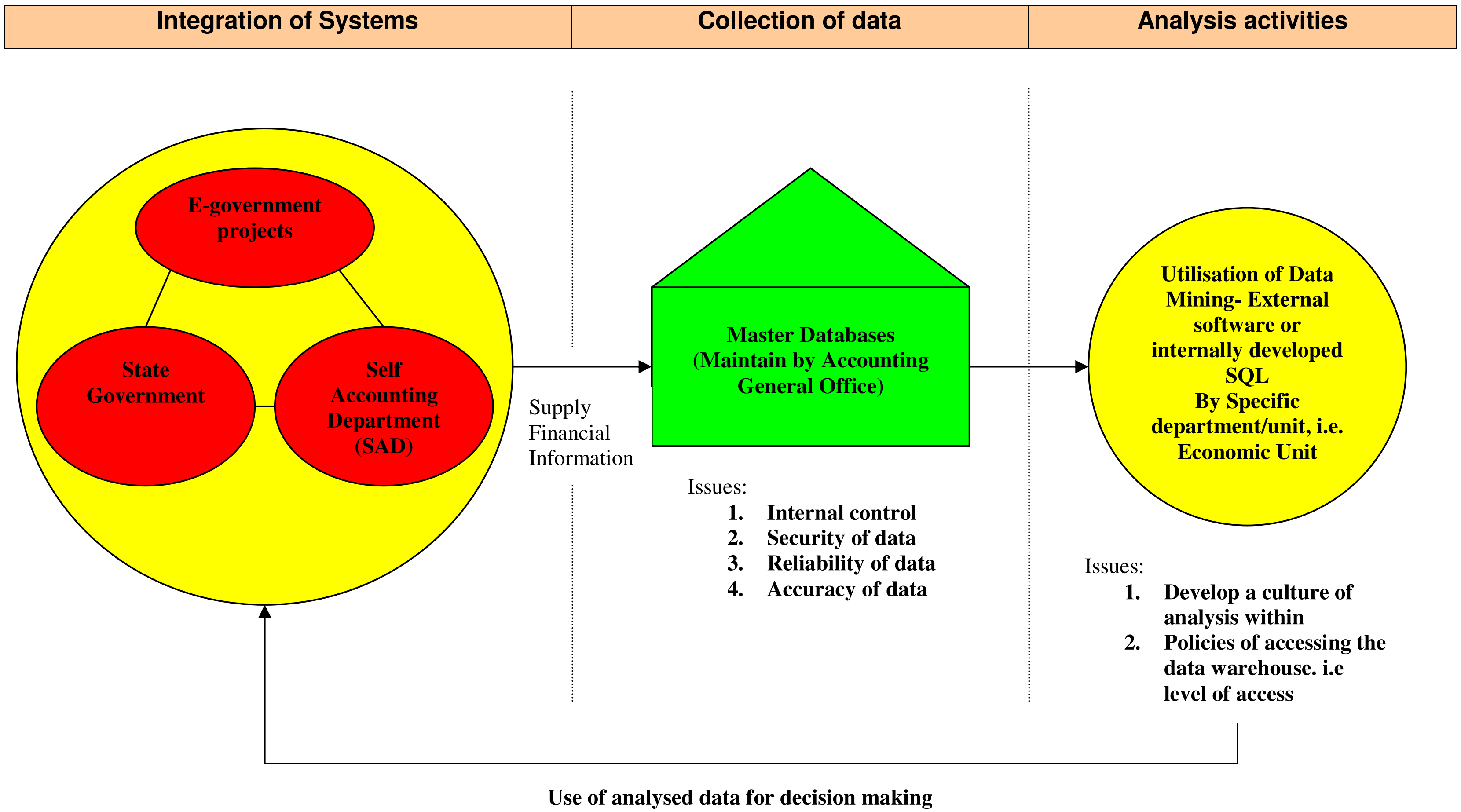
This section presents the data analysis related to Research Question Four.

Research Question 4: *What model would allow the Malaysian public sector to better apply data mining techniques to ensure high quality of information in accounting information systems?*

This question is intended to identify a potential model for adoption within the Malaysian public sector environment that would result in the successful implementation of data mining technology. Discussions resulting from interviews suggest that to better implement data mining technologies an appropriate model (Figure 5.2) for the public sector would be an integrated system with a centralised data warehouse. This model would need to incorporate the working culture, procedures and emphasise the importance of financial data in decision making process within the public sector.

In the development of the model the first phase is the integration of systems that currently operate within the public sector. Abu Bakar *et al.,* (2001) note that systems integration in the public sector is not a new phenomenon in Malaysia. E-Government initiatives have increased the importance of systems integration. Integration refers to the ability to allow department and between department computers to link with each other and share data and information (Abu Bakar *et al.,* 2001). In this study, the integration between E-Government projects, state government accounting departments, and also self-accounting department (SAD) with Accountant General Head Quarters (HQ) were suggested to bring the financial and accounting related data into one data warehouse for ease of access. That is, all systems from all electronic governments' project, data from statement governments systems and the self accounting department (SAD) would have structures in which the systems could communicate with each other.

Figure 5.2: Data mining utilisation model



As one interviewee commented '*when we talk about a method or model to be used, it is actually interrelated with many systems but if one of this system failed, it will normally impair the whole system. Although it is not a complete failure, it would not give a good and thorough services. What is important in government is, integration between E to E (which refers to electronic projects), make sure it can communicate with each other. Supposedly, we have one major, big E, and all under that can talk to each other.'* Another interviewee commented that all those systems contribute to a central collation to create a master database *'actually in government, we can do it, when we want to make any decision we should have one master database, what we have now is, state governments have their own system, accountant general office also has theirs, and also self accounting department (SAD). If it can be collected into one storage, which is centralise and use those information for data mining...that's ideal.'*

Another interviewee also sees that his department is ready to play a major role in collecting all this data for data mining activities within the government's accounting systems '*For finance, I should think that we already have a structure for financial information, we can collect all information, all the sources of that information. So others can link directly to our department's data warehouse.'* This department is the central department that collects the government's financial data '*but in terms of the model, how we are going to do, for financial data, we already have it. It's because all financial matters will reflect to our department. The entire governments department will come back to us, we have all the information'*. Concurrently with the master database issues such as monitoring, and the security of data to ensure the reliability and accuracy of that data is required. Given that departments often need to access 'the same data' there is a need for the government to have one major centralised data warehouse for accounting and financial data. This will make the concepts of one-stop-shop to government services will be convenient and less confusing (Abu Bakar *et al.,* 2001)

Once the issue of integration and one centralised data warehouse has been established, which managed by one particular department in this case Accountant General Office, any further data mining activities, analysis and scrutiny of data would be made possible for an authorised personnel and users. Data mining activities taking place should use the same data from this master database in assisting decision making by either adopting external and independent software such as ACL or developed internally within the databases. One interviewee suggests*' maybe SQL is the most perfect for interrogation, most SQL were developed within the system itself, for example with e-spkb, SQL will interrogate it own databases. If we have a system which can create its own SQL so we don't have to use external software to interrogate its databases. So, we just have only one complete system...'*

However, in the case of accessing the master database, interviews suggested that a policy on level of access has to be developed. Not all departments will have similar privilege to access the data warehouse as one of the interviewee claimed *'There is a policy, if it requires to access, we can provide according to the needs, for example Bank Negara (central bank of Malaysia), or Auditor General offices, we give accordingly.'*

One interviewee even suggested that the utilisation of data mining activities should be carried out by one department, for example economic department or a unit within ministry to supply the results of analysis rather than every single unit performing such analysis. *'For analysis, we put one section maybe in economic section, we supply data we analyse, we can only access to certain level, then that it's a good system. We don't need everything here, meaning that if we want to supply payment receipt so we provides them with that for analysis, there is no problem of getting access to that analysis. That is the system that I wanted. We don't have to be an expert in everything, but we know where we can get information. There is no point if we have loads of information but can't use it, that useless, can't be analysed, we should have limits...different level of decision making…which information is useful...according to the level...'*

Another issue which relates to the culture of decision making process is also important. Since the culture of making a decision based on financial data was not very common in the public sector in Malaysia, one interviewee commented that :

'*I take an example of the accounting general's office, they have all the financial information, so they should use this information thoroughly in their decision making. So, as for now, that information was not fully utilised, meaning that, those figures produced in summaries were not fully use in decision making activities, maybe it's there but that is not our culture yet...'* Therefore, in making sure the successful of data mining utilisation, the culture of making use of data and results produce by data mining activities should be created and continuously supported by the top management.

To allow the public sector to better apply data mining techniques, an ideal model will need to have a good management of data warehouses utilising a centralised data warehouse. The application of data mining, and access to that data warehouses would be hierarchical according to the level of management and types of access required to perform the job function. In terms of data mining software this can be developed in-house of from another more generic source but would need to be able to be used for various purposes at different levels, be easy to use and understand, be able to be upgraded and be cost effective.

5.10 Conclusion

This chapter presented descriptive, statistical results and interview data that were conducted for this research. The descriptive statistics has shown that most of the respondents gained their AIS experiences while working in government. Many of the respondents were not aware of data mining or not sure of the utilisation of data analysis software. Respondents identified influencing factors for utilising data mining and reasons for not utilising it. Each of the major research questions were analysed. In the next chapter hypotheses which related to those research questions are tested and discussed.

Chapter 6

Results, Findings and Hypotheses Testing

6.1 Introduction

In the previous chapter the descriptive quantitative results together with interview comments were discussed. It was found that there is readiness toward accepting data mining technology although there was low level of awareness about such technology. The results indicated that there are positive perceptions of the impact data mining technology could have on the performance of the Accounting Information Systems (AIS) and decision making. The ability to utilise data mining was identified to be an important criteria in a good accounting system. In this chapter the hypotheses posed in this study are analysed.

6.2 Data analysis: Hypothesis Testing

6.2.1 Influencing issues in decision to utilise data mining

Hypothesis One (H1) posed that issues such as technological, organisational, human resources and external have it influences in the decision to utilise data mining technologies within public sector.

Hypothesis One

H1: Technological, Organisational, Human Resource and External issues are significant influences in the decision to utilise data mining technology.

In this section, the hypothesis related to the influences that lead to the implementation of data mining technologies in public sector departments were analysed. These four issues represent factors that have been identified as potentially influential in the decision to adopt technology within the public sector. Responses are summarized in Table 6.1 below. Responses to the technological issues were positive in that over

80% of respondents agreed with the issues identified. Issues such as technical support, compatibility of software and a department with an appropriate ICT infrastructure are likely to be influential in any decision to employ data mining. Over 90% of respondents indicated agreement with the organisational issues agreeing that it was important to have the support of top management and adequate financial resources to support data mining technology.

Table 6.1: Factors influencing decision to utilise data mining - % of agreement

Influencing Factors	Agreement (By Number of Responses and %) n=25		
	Strongly Agree	Agree	% of Agreement
Factors (Technological Issues)			
11.1 Adequate technical support from vendors	7	14	84
11.2 Compatibility of software with existing operating systems	11	10	84
11.6 Up to date ICT infrastructure	11	10	84
Factors (Organisational Issues)			
11.3 Full support from top management	16	8	96
11.10 A sufficient financial resources	13	9	88
Factors (Human resources issues)			
11.4 Effective and adequate training for staff	15	8	92
11.5 Technology savvy staff	8	13	84
Factors (External Issues)			
11.7 Changes in management trend within private sector	5	5	40
11.8 Directives from politicians	2	2	16
11.9 In attempt to ensure public accountability	13	11	96

Human resource issues such as adequacy of training and staff with technology skills were important. There was agreement by 83% to 92% of respondent respectively that this was an influential factor to any decision to employ data mining technologies. The influence of external issues such as changing trends in management trend in private sector and the influence of politicians not appears to be that influential in the decision to employ data mining. There are quite a significant number of respondents adopted a neutral view on these issues. However, efforts to ensure public accountability were rated highly as a potential influence.

Individual t-test on every each statements representing technological issue were positive and significant. Adequate technological support from vendors (statement 11.1, p(24)=8.411, <.001), compatibility of software with existing operating systems (statement 11.2, p(24)=8.683, <.001) and having an up to date technological infrastructure (statement 11.6, p(24)=9.560, <.001) (Table 6.2).

Table 6.2 Individual t-test: Technological influences

Factors	Descriptive Statistics			t-tests (two-tailed/test value=3)	
	Mode	Median	Mean	T value	Sig
11.1 Adequate technical support from vendors	4.00	4.00	4.1200	8.411	.000
11.2 Compatibility of software with existing operating systems	5.00	4.00	4.2800	8.683	.000
11.6 Up to date ICT infrastructure	4.00	4.00	4.3200	9.560	.000

Technological issues such as technical support, compatibility of software and up-to-date infrastructure were influence the decision of data mining adopters in public sector. It does show it is important for departments to have up to date infrastructures, to choose compatible software with current operating systems and to have good and reliable technical support from vendors.

Table 6.3: Transformed Technological issues in decision to utilise data mining

Descriptive Statistics			t-tests[33] (two-tailed/test value=3)	
Mode	Median	Mean	T value	Sig
4.33	4.3333	4.2400	10.967	.000

Statements 11.1, 11. 2 and 11.6 which representing technological issues were found to be a reliable measure of technological issues in this study (Cronbach's Alpha .737)[34]. These three statements were combined to create a new single variable to represent technological issues. T-test on transformed variable produced a positive and significant result which shown in Table 6.3 above *($t(24)=10.967$, $p<.001$).* The

[33] One-Sample t-Test was used with 3 as the 'test value' which represents a midpoint of agreement. Value above 3 suggests that respondents generally agreed that the technological issue was an important influence in decision to utilise data mining.
[34] Reliability Analysis is shown in Appendix Seven

transformed variable indicates that technological issues are significantly important in the decision to utilise data mining.

Statement 11.3 (Full support from top management) and 11.10 (A sufficient financial resources) which represents organisational issues were also produce a positive and significant results ($t(24)=13.856$, $p<.001$ and $t(24)=11.066$, $p<.001$) respectively. (Table 6.4). It indicates that commitment from top management definitely will increase the opportunity of larger allocation of finance for any project within public sector department which than may influence the decision to utilise technological innovation and changes in the department.

Table 6.4 Individual t-test: Organisational influences

Factors	Descriptive Statistics			t-tests (two-tailed/test value=3)	
	Mode	Median	Mean	T value	Sig
11.3 Full support from top management	5.00	5.00	4.6000	13.856	.000
11.10 A sufficient financial resources	5.00	5.00	4.4400	11.066	.000

In the further analysis of organisational issues, statements 11.3 (support of top management) and 11.10 (provision of adequate financial resources) found to be influential were transformed. A transformation into a new single variable (organisational issue) was found to be significant, the t-test revealed a result of ($t(24)=14.341$, $p<.001$) (Table 6.5).

Table 6.5: Transformed Organisational issues in decision to utilise data mining

Descriptive Statistics			t-tests[35] (two-tailed/test value=3)	
Mode	Median	Mean	T value	Sig
5.00	4.5000	4.5200	14.341	.000

[35] One-Sample T-Test was used with 3 as the 'test value' which represents a midpoint of agreement. Value above 3 suggests that respondents generally agreed that the organisational issue was an important influence in decision to utilise data mining.

This issue does appear to influence the decision to utilise data mining in public sector. The result shows that top management support and adequate financial resources plays an important role in decision to adopt such technology.

Individual t-test on statements 11.4 and 11.5 representing human resource issue also shows a positive and significant influence toward decision to employ data mining: Effective and adequate training for staff (statement 11.4, $t(24)=11.635$, $p <.001$) and technology savvy staff (statement 11.5, $t(24)=8.430$, $p<.001$). This result shows that decision to utilise data mining technology also influenced by the existence of an effective and adequate training staff and also by having staff who are technologically savvy.

Table 6.6: Individual t-test Human Resources influences

Factors	Descriptive Statistics			t-tests (two-tailed/test value=3)	
	Mode	Median	Mean	T value	Sig
11.4 Effective and adequate training for staff	5.00	5.00	4.5200	11.635	.000
11.5 Technology savvy staff	4.00	4.00	4.1600	8.430	.000

Both statements (11.4 and 11.5) were transformed to a single variable which represent human resources issue. The t-test on human resources issue shown a significant result ($t(24)=11.353$, $p<.001$) (Table 6.7). Human resources issue appears to influence the decision to utilise data mining in public sector. As expected, human capital is also important as one of the recipe of technological success within organisation.

Table 6.7: Transformed Human Resources issues in decision to utilise data mining

Descriptive Statistics			t-tests[36] (two-tailed/test value=3)	
Mode	Median	Mean	T value	Sig
5.00	4.5000	4.3400	11.352	.000

[36] One-Sample t-Test was used with 3 as the 'test value' which represents a midpoint of agreement. Value above 3 suggests that respondents generally agreed that the human resource issue was an important influence in decision to utilise data mining.

In the case of external issue, it represented by three factors (Statement 11.7, 11.8 and 11.9). An individual t-test on those three factors shown positive and significant: Changes in management trend within private sector (Statement 11.7, $t(24)=2.493$, $p<.05$) and an attempt to ensure public accountability (Statement 11.9, $t(24)12.629$, $p<.001$). However, directives from politician (Statement 11.8) does not appears to be significant influence for the decision to employ data mining ($p(24)=-.592$, sig=.559). This insignificant result would appear to be due to the neutral position taking by the majority of respondents in expressing a view as to whether politicians have an influence to their decision (sixty percent or 15 responses were neutral), while only sixteen percent (4 respondents) agreed to that statement. However, comments from interviews suggest that politician instruction and intervention does have some influence in the decision taken by public sector organisation.

Table 6.8 Individual t-test: External influences

Factors	Descriptive Statistics			t-tests (two-tailed/test value=3)	
	Mode	Median	Mean	T value	Sig
11.7 Changes in management trend within private sector	3.00	3.00	3.4800	2.493	.020
11.8 Directives from politicians	3.00	3.00	2.8800	-.592	.559
11.9 An attempt to ensure public accountability	5.00	5.00	4.4800	12.629	.000

Given the significant result and strong agreement from the interviews, these three statements were further analysed. Statements (11.7, 11.8 and 11.9) were found to be a reliable measure of external issues in this study (Cronbach's Alpha .684)[37]. Transformation of these three statements which representing external issues yielded a positive and significant t-test ($t(24)=4.477$, $p<.001$) (Table 6.9).

Table 6.9: Transformed External issues in decision to utilise data mining

Descriptive Statistics			t-tests[38] (two-tailed/test value=3)	
Mode	Median	Mean	T value	Sig
3.67	3.6667	3.6133	4.477	.000

[37] Reliability Analysis is shown in Appendix Seven

[38] One-Sample t-Test was used with 3 as the 'test value' which represents a midpoint of agreement. Value above 3 suggests that respondents generally agreed that the external issue was an important influence in decision to utilise data mining.

The results indicate that external issues can be influencing the decision to utilise data mining in public sector. Although, it seems respondent little bit reluctant to actually say their stand on political issues for example (vast majority of them tend to be neutral), the external issues as a whole did have an influence in the decision to utilise such technology. The trend in private sector for example has been influencing the way of public sector run its business and activities. A concept such as knowledge management for example was not unfamiliar within public sector. Ensuring the accountability of public organisation has always being the important objective by providing a good services to the public and uphold the department's accountability and its integrity.

Table 6.10: Influencing factors in the decision to utilise data mining technologies

Influence Factor	Statements	Transformed and One Sample t-test	Hypothesis Supported
		Positive and Significant	
Technological	11.1 Adequate technical support from vendors 11.2 Compatibility of software with existing operating systems 11.6 Up to date ICT infrastructure	Yes	Yes
Organisational	11.3 Full support from top management 11.10 A sufficient financial resources	Yes	
Human resources	11.4 Effective and adequate training for staff 11.5 Technology savvy staff	Yes	
External	11.7 Changes in management trend within private sector 11.8 Directives from politicians 11.9 In attempt to ensure public accountability	Yes	

Overall, the descriptive statistics and series of t-test indicate that these four issues influence the decision to utilise data mining in the public sector. Technological, Organisational, human resource issues and external issues were found to be significant in the decision to adopt data mining technology. Political influence, as an external issue was also indicated through interview to influence the decision to utilise technology within public sector. Hypothesis One (H1) is supported.

6.2.2 Reasons in decision not to utilise data mining

In this section, the hypothesis related to the reasons not to utilise data mining technologies were analysed. There were three issues identified which were technological, organisational, and human resources.

Hypothesis Two

H2: Technological issues, organisational issues and human resource issues are significant reasons in the decision not to utilise data mining

Respondents who indicated that their departments were not adopting data mining indicated reasons classified as technological, organisational and human resource. The responses are shown in Table 6.11 below. Responses to the technological reasons were between thirty percent (reason 12.7) to fifty-six percent (reason 12.6) while reason 12.1 have agreement about forty-eight percent. Almost half of the responses were seated at neutral position. Forty to forty-four percents responses was neutral to these reasons which represent technological issues.

Table 6.11: Reasons for not utiling data mining-% of agreement

Reasons	Agreement (By Number of Responses and %) n = 25		
	Strongly Agree	Agree	% of Agreement
Technological Reasons			
12.1 Satisfied with current analysis method	0	12	48
12.6 Difficult to select appropriate software	1	13	56
12. 7 Too complex and time consuming	2	7	36
Organisational Reasons			
12.4 Costly to implement new technology	2	15	68
12.5 Lack of top management support	2	9	44
12.8 Lack of management policies	2	8	40
12.9 Having more pressing problems	3	6	36
Human Resources Reasons			
12.2 Lack of expertise to implement data mining	4	10	56
12.3 Lack of awareness about data mining	6	9	60

In the case of organisational reasons, there reasons (12.5, 12.8, and 12.9) had an agreement ranging between thirty to forty percent of respondents. However, for reason 12.4, there were more than sixty percent of respondents who agreed that cost was an important reason why they would not utilise such technologies within its department.

For human resources perspective however, they showed strong agreement toward those two reasons (12.2 and 12.3) which represented by fifty-two and fifty-six percent of agreement respectively. It indicates that lacking in specific expertise in implementation of data mining (statement 12.2) and lacking of awareness about such technology (statement 12.3) were important reasons why they would not utilise data mining technology. Both items which contribute to the human resource issues shown that this issue is important reasons for not utilise data mining.

Technical aspect of technology such as inherent difficulties of the software, complexity, time consuming, and difficulties in selecting appropriate software packages has been cited as a reason for not adopting new technology (Chung *et al.,* 1997). In this study, satisfaction with current software (statement 12.1), difficulties to select appropriate software (statement 12.6), and complexity and time consuming (statement 12.7) were used to represent technological reasons.

Among those three statements representing technological issues, it was found that a difficulty in selecting an appropriate data mining was the most contributing reason. Further one-sample t-test (Table 6.12) for this single statement also produced a positive and significant result (Difficult to select appropriate software (Statement 12.6), $t(24)=4.303$, $<.001$). This indicates that the technological reasons for not utilising such technology related to difficulties in selecting a good and appropriate software which suitable and practical. As for statement 12.1 (Satisfied with current analysis method), the t-test found to be close to significant ($t\ (24)=1.995$, $p=.058$). This reflects the level of satisfaction on current systems they currently have in place as found in Chapter 5, that majority of respondents were expressing their satisfaction with it. For statement 12.7 (Too complex and time consuming) however, the t-test shows an insignificant (t(24)=1.044, p=.307) result. The majority of respondents took a neutral stand with only nine respondents agreeing (Table 6.12). This has contributed to the insignificant result. However, comments from interviews did mention issues such as time consumption to implement such technology.

Table 6.12: Individual t-test: Technological reasons

Reasons	Descriptive Statistics			t-tests (two-tailed/test value=3)	
	Mode	Median	Mean	T value	Sig
12.1 Satisfied with current analysis method	4.00	3.00	3.3200	1.995	.058
12.6 Difficult to select appropriate software	4.00	4.00	3.5600	4.303	.000
12.7 Too complex and time consuming	3.00	3.00	3.2000	1.044	.307

Statements representing technological issue were found to be reasons for not utilising such technology. Combining those statements a transformed technological reason variable resulted a positive and significant t-test result, (t(24)=3.311, p=.003) (Table 6.13).

Table 6.13: Transformed Technological reasons for not utilising data mining

Descriptive Statistics			t-tests[39] (two-tailed/test value=3)	
Mode	Median	Mean	T value	Sig
3.00	3.3333	3.3600	3.311	.003

A number of studies have found that top management support has been a key factor influencing the adoption of a new information technology. Having a good support from top management usually leads to assistance to acquire financial support, human resources and other related resources (Dahlan *et al.,* 2002, Chang *et al.,* 2003, Hwang *et al.,* 2004). Lack of such support would then become a reason for unsuccessful or discouragement of the implementation of technological innovations or change within the organisation. This study also found that lack of top management and financial reasons did significantly contribute to the organisational reason for not utilising such technology. A t-test was conducted on each statement produced significant results

[39] One-Sample t-Test were used with 3 as the 'test value' which represents the midpoint between agreement and non-agreement. A value above 3 suggest that respondents generally perceived that *'Technological reasons'* were significant reasons in the decision not to utilise data mining technology within the AIS in the department.

for the two statements (Costly to implement new technology, statement 12.4, t(24)=4.543, p<.001 and lack of top management support, statement 12.5, t(24)=2.092, p<.05 (Table 6.14).

Table 6.14: Individual t-test: Organisational reasons

Reasons	Descriptive Statistics			t-tests (two-tailed/test value=3)	
	Mode	Median	Mean	T value	Sig
12.4 Costly to implement new technology	4.00	4.00	3.6800	4.543	.000
12.5 Lack of top management support	3.00	3.00	3.3600	2.092	.047
12.8 Lack of management policies	3.00	3.00	3.2800	1.572	.129
12.9 Having more pressing problems	3.00	3.00	3.2400	1.141	.265

For statement 12.8 (lack of management policies) and 12.9 (having more pressing problems) however, insignificant results were found. This is because once again, the majority of respondent took a neutral stand on those statements. However, percentage of agreement toward these statements, for example forty percent of respondent agrees that lack of management policies (statement 12.8) and 36% agrees on having more pressing problems (statement 12.9), indicates that it can contributes in representing organisational issue as a reasons for not utilising data mining within the department.

Those four statements were transformed into a transformed organisational reason variable. Table 6.15 below yielded a positive and significant (t(24)=3.228, p<0.05) which indicating that the organisational issue contributes to the decision not to utilise data mining within the public sector.

Table 6.15: Transformed Organisational reasons for not utilising data mining

Descriptive Statistics			t-tests[40] (two-tailed/test value=3)	
Mode	Median	Mean	T value	Sig
3.00	3.2500	3.3900	3.228	.004

[40] One-Sample t-Test were used with 3 as the 'test value' which represents the midpoint between agreement and non-agreement. A value above 3 suggest that respondents generally perceived that *'Organisational reasons'* were significant reasons in the decision not to utilise data mining technology within the AIS in the department.

In the case of human resource reasons, both statements: lack of expertise to implement data mining (statement 12.2) and lack of awareness about data mining, (statement 12.3) representing the issue has also shown a positive and significant result ($t(24)=3.720$, $p=.001$) and ($t(24)=4.106$, $p<.001$) respectively (Table 6.16).

Table 6.16: Individual t-test: Human Resource reasons

Reasons	Descriptive Statistics			t-tests (two-tailed/test value=3)	
	Mode	Median	Mean	T value	Sig
12.2 Lack of expertise to implement data mining	4.00	4.00	3.6400	3.720	.001
12.3 Lack of awareness about data mining	4.00	4.00	3.7600	4.106	.000

Both two statements (12.2 and 12.3) were transformed to create one variable representing the human resources issue. The transformed variable was also resulting a positive and significant ($t(24)=4.041$, $p<.001$) (Table 6.17) indicating that human resources also was the main reasons in decision for not utilising data mining technology in public sector organisations.

Table 6.17: Transformed Human Resources reasons for not utilising data mining

Descriptive Statistics			t-tests[41] (two-tailed/test value=3)	
Mode	Median	Mean	T value	Sig
3.00	4.0000	3.7000	4.041	.000

It stressed the importance of employees or human capital skills and awareness about any technological advancement brought into the organisation. It supports the study by Sabourin (2001) who found that a shortage of skilled workers was an impediment to the usage of advanced technology. Often in the adoption of technological advances skills of the required type are in short supply. The lack of expertise is identified as a

[41] One-Sample t-Test were used with 3 as the 'test value' which represents the midpoint between agreement and non-agreement. A value above 3 suggest that respondents generally perceived that *'Human resource reasons'* were significant reasons in the decision not to utilise data mining technology within the AIS in the department.

possible reason that would hinder a public sector department along with a lack of staff awareness in the decision to utilise data mining technology.

Table 6.18: Reasons in the decision not to utilise data mining technologies

Reasons	Statements	Transformed and One Sample t-test	Hypothesis Supported
		Positive and Significant	
Technological	12.1 Satisfied with current analysis method 12.6 Difficult to select appropriate software 12. 7 Too complex and time consuming	Yes	Yes
Organisational	12.4 Costly to implement new technology 12.5 Lack of top management support 12.8 Lack of management policies 12.9 Having more pressing problems	Yes	
Human resources	12.2 Lack of expertise to implement data mining 12.3 Lack of awareness about data mining	Yes	

The descriptive statistics and series of t-test above indicate that these three issues did contribute to the reasons in the decision not to utilise data mining in the public sector. A difficulty in selecting appropriate software for data mining was the main technological reason while lack of top management support and limited financial resources represented organisational issues. Human resources issue was found to be the reasons for not pursuing data mining technology. Lack of expertise and awareness about such technology was found to be contributing reasons for not utilising the technology. Hypothesis Two (H2) is supported.

6.2.3 Data Mining knowledge and intention to utilise

Having knowledge about data mining and perceptions of the impact or benefits that data mining could bring to the organisation, may have been driver in the intention to adopt such technology. Therefore it was hypothesised that there will be a relationship between understanding the benefits that data mining could bring to the organisation and the intention to adopt these technologies.

Hypothesis Three

H3: There is a significant relationship between knowledge of data mining and the intention to utilise data mining tools.

In seeking to test the hypothesis, two variables - knowledge and the intention were used in the analysis. Correlation and cross tabulation were adopted to investigate the hypothesis. Table 6.19 summarized the strength of association between knowledge about data mining and intention to utilise data mining tools. All measurements of strength show a moderate (i.e. Gamma=.462) significant association between the variables. In the case of Gamma, a moderate positive association suggesting that as the knowledge of data mining increase it would have a positive impact on the intention to utilise data mining tools in the future.

Table 6.19: Strength of association: data mining knowledge and intention to utilise

Measure of strength	Value	Approx. Sig.
Kendall's tau-b	.223	.028
Gamma	.462	.028
Spearman rho	.243	.038

Kendall's tau and Spearman's rank order correlation (*rho*) also indicate a significant results (Kendall=.223 p=.028 and rho=.243, p=.038). These measurements also appropriate to test the hypothesis as suggested by Leech *et al.,* (2005). Hypothesis Three (H3): Knowledge about data mining among the officers and staff has a significant relationship with the intention to utilise data mining tools, is accepted.

6.2.4 Data mining readiness between gender

Gender differences have generally been investigated in the context of individual adoption and sustained usage of technology in the workplace (Venkatesh & Morris 2000, Zin *et al.,* 2000, Kay 2006). Results of investigations have been mixed. In some cases, male have been reported to possess higher skill levels than females in operating systems, database software, web page creation and programming (Kay, 2006). In the learning institution environment in a Malaysian University, researchers found that there was a significant difference in computer literacy level between male and female students (Zin *et al.,* 200) where male had greater self-perceived control, skill and better ability to repair. Dahlan *et al.,* (2002) also found that male employees seem to more ready to accept data mining technologies as compared to their female counterpart. Ventakesh and Morris (2000) however reported that females were found to be more influenced by the perception of ease of use in the decision to adopt new technology. This suggests that attitudes toward computer not affected by gender as found by Busch (1995).

In the Malaysian public sector departments it is hypothesised that there will be differences in attitudes and readiness toward technology (in this case data mining) between genders.

Hypothesis Four

H4: There is a significant gender difference in the readiness to adopt data mining technology.

In assessing the belief that in the Malaysian public sector readiness is the same for both genders an independent-sample t-test was adopted employing the SPSS-Compare Mean Procedure. Prior to undertaking testing the data was checked to ensure the distribution was normal and assumptions[42] for using t-tests were met. The results for readiness between genders are shown in table 6.18 below. In this case, mean overall readiness for female (M=3.96, SD=0.56, n=71) was slightly lower than the mean overall readiness for male (M=4.04, SD=0.44, n=61). As can be seen, Levene's[43] test showed no significance difference in the variances (F=2.866, p=0.093) between male to female respondents. An equal variance statistic was

[42] See Appendix 6.1
[43] Levene's Test used to assess as whether variance between standard deviation between two groups (in this case male and female) is significantly difference. In the case of non-significant Levene's Test, an equal variance statistics was consulted for t-Tests.

assumed and adopted in this independent samples t-test. This is because given the non-significant of Levene's test which indicates that the variances of the two groups are not significantly different, so the homogeneity of variance assumption wasn't violated (Colman *et al.,* 2006). The result of t-test was also not significant (significance level of this test is greater than the acceptable level of significant, which is 0.05), therefore, null hypothesis is not rejected and Hypothesis Four (H4) is not supported.

Table 6.20: Descriptives Statistics, Levene's test and t-test of readiness vs. gender

Sex	n	Mean	Std. Deviation	Levene's Test for Equality of Variances		t-test for Equality of Means		
				F	Sig	t	df	Sig (2 tail)
Male	61	4.0426	.44402	2.866	.093	.946	130	.346
Female	71	3.9592	.55281					

The findings may imply that technological experiences and personal involvement with such technology which have been given similar opportunity between genders might as well eliminate differences between it. The public sector in Malaysia, it has been an equal opportunity employment for some time.

6.2.5 Data Mining readiness and education

Ventakesh and Morris (2000) investigated the impact between the levels of education in the context of technology acceptance. It is believed that the level of education impacts on one's perception of the world around us including technology innovation and adoption. This study seeks to establish whether there is a relationship between the level of education and respondents readiness to adopt data mining. It is believed that the higher the level of education the higher the level of readiness to adopt new technology will be as a better educated person is often more positive toward exposure to new ideas and in this case to data mining concepts. It is also likely in previous studies such a person may well have been exposed to developing technology.

Hypothesis Five

H5: There is a significant difference between different levels of education in their readiness toward data mining technology.

This hypothesis is analysed from two perspectives. First to perform a one-factor independent measure ANOVA to find whether there is any significant difference between mean readinesses among the three level of education identified. Table 6.21 shows that an ANOVA[44] resulted in a significant different between level of education possessed by respondents on their readiness to accept data mining technology in their working place, $F(2,129)=7.934$, p=.001.

Table 6.21: ANOVA: Data mining readiness vs. level of education

Level of education	n	Mean	Std. Deviation	ANOVA results	
				F	Sig
Master's degree	27	4.3111	.36829	7.934	.001
First Degree/equivalent	72	3.8792	.50933		
Diploma and lower	33	4.0000	.49497		

Following the significant results above, further analysis through Post-Hoc Multiple Comparison were considered in the second perspective of analysis. Looking at the groups mean (see Table 6.21) shows us that there is a different mean of readiness between different levels of education. Tukey post hoc test (Table 6.22) indicated that there is a significant different between the holders of masters degree and the other two groups. Although it seems that diploma and lower groups have a higher mean than first degree groups, Tukey post-hoc test shows no significant different between them. The result of this test can be summarized as follows:

- Officers with master degree had better readiness than officers who hold first degree or a lower qualification.
- Officers with first degree had comparable readiness to officers who had diploma or a lesser qualification.

[44] The variable was tested to be normally distributed so that it is suitable for ANOVA, see Appendix 6.2

Table 6.22: Tukey post-hoc test for level of education mean of readiness

(I) Education	(J) Education	Mean Difference (I-J)	Sig.
Master's Degree	First Degree/Equivalent	.43194	**.000**
	Diploma and lower	.31111	**.037**
First Degree/Equivalent	Master's Degree	-.43194	**.000**
	Diploma and lower	-.12083	.458
Diploma and lower	Master's Degree	-.31111	**.037**
	First Degree/Equivalent	.12083	.458

Overall, the level of education would seem to play a role in a department's readiness to employ data mining technology. Thus, Hypothesis Five (H5), that there is a significant difference between different levels of education in their readiness toward data mining technology, is supported.

6.2.6 Data Mining readiness and job function

Another aspect of individual differences which is explored by this study is job function. Job functions and job level have been reported to correlate with difference of cognitive style (Taylor, 2004). A cognitive style is one of the perspectives of individual differences which have significant effects on information system design and use. Taylor (2004) suggests that even in the same organisation, cognitive style would be different between different job function and level. Allinson & Hayes (1996) suggests there are differences in cognitive style between different job functions. As a cognitive style would reflect the way and thinking process, it argued that would also reflect their perception. People may also actually change their attitudes, perceptions and behaviours to fall in line with the consensus of the group (Lembke & Wilson, 1998). In this study, all job function undertaken by all respondents is relates to an accounting information systems, it mainly represented by three groups - accountants, auditors and information technology personnel. It is proposed that these difference functions would have a difference in their cognitive style and perception toward accepting data mining technology.

Therefore Hypothesis Six (H6) was posed and is now tested:

H6: There is a significant difference between the different job functions of respondents and their readiness toward adopting data mining technology.

Four main job functions were identified in the survey. In order to investigate whether there are any differences in readiness towards data mining among these job function, analysis of variance (ANOVA) was employed. The results of ANOVA are summarized in table 6.23 below.

Table 6.23: ANOVA: Data mining readiness vs. job function

Job function	n	Mean	Std. Deviation	ANOVA F	ANOVA Sig
Accounting	49	4.0347	.46929	.638	.592
Finance	19	3.9789	.55536		
Information Management	9	4.2333	.31225		
Auditing	39	4.0410	.42718		

From the table there seem to be minimal differences of mean readiness among those job function which ranged between 3.98 and 4.23. To be certain statistically, ANOVA test result show that the differences was not significant. F value of .638 is not significant (p=0.592). Results above suggests that there is no differences in their readiness to accept data mining between difference job function confirming the stereotypical perceptions that accountants and financial related managers are highly analytic orientation judgment based on reasoning and analysis (Taylor, 2004) and might have similar perception of this technology. A similar no significant differences in readiness among difference job functions were also found in banking sector (Dahlan *et al.,* 2002). Thus, the Hypothesis Six (H6), that there is a significant difference between job function in their readiness towards data mining technology is not substantiated.

6.2.7 Data Mining readiness and experience in AIS

A number of studies (see Davis, 1989, Agarwal & Prasad, 1999, Ventakesh & Morris, 2000) have argued that attitude toward technology is positively related to experience.

Ventakesh and Morris (2000) suggest that individuals have a better assessment of the benefits and cost associated with technology as direct experience with technology increases over time. Agarwal and Prasad (1999) found that extent of prior experiences with similar technologies had a positive association with perception on easy to use. They also found that workforce tenure did not have an effect on perception or beliefs. However, in this study, it proposed that working tenure in the area of AIS has exposed employees to the use of information technology for example computer based accounting systems. Interview comments from the previous chapter also confirm that the involvement of computer technology in the everyday working environment is inevitable. In the department continuous programs of training on information systems for example, increase exposure toward technology innovation. Participating in training was found to be positively associated with perception of usefulness brought by the technology (Agarwal & Prasad, 1999). For the purpose of this study, it proposed that the longer a respondent is involved in the Accounting Information System, the more information technology experience they possess, and then the more positive their attitude toward accepting data mining technology will be. It is posed:

Hypothesis Seven

H7: There is a significant difference between experience in involvement in the AIS (number of years) and readiness to implement data mining.

ANOVA was adopted to compare the readiness to adopt data mining technologies with years of experience working in the accounting information system. The results (Table 6.24) show that there is a significant difference of readiness between the three experience groups ($F(2,129)=7.218$, $p=.001$). The result also shows that officers with four to six years of experience scored the highest mean of readiness (mean=4.29), post hoc test (see table 6.25) shown that this group was significant different from the other two groups. The results also indicated that groups with more years experience (> 6 years) have a comparable readiness with those with more limited (< 4 years) experiences.

Table 6.24: ANOVA: Data mining readiness vs. experience in AIS

Year of experience	n	Mean	Std. Deviation	ANOVA	
				F	Sig.
< 4 Years	65	3.8831	.55073	7.218	.001
4-6 years	31	4.2806	.47358		
>6 years	34	3.9529	.33955		

A finding from the Tukey post-hoc (Table 6.25) indicates that years of experience do not necessarily equate with readiness to adopt data mining technology. Other factors such as cognitive style and job function itself may play a role. For example, officers with more than 6 years of experience may have moved to more senior managerial positions (i.e. Head of Department) and be less involved with hands-on accounting work.

Table 6.25: Tukey post-hoc test for experience in AIS mean of readiness

(I) Experience in AIS	(J) Experience in AIS	Mean Difference (I-J)	Sig.
< 4 Years	4-6 years	-.39757(*)	**.001**
	>6 years	-.06986	.776
4-6 years	< 4 Years	.39757(*)	**.001**
	>6 years	.32770(*)	**.020**
>6 years	< 4 Years	.06986	.776
	4-6 years	-.32770(*)	**.020**

A finding also implies that group of employees with 4 to 6 tenure was the most ready and significantly differs from the other two groups. This indicates that during this period they were very comfortable with their work understanding the systems and benefits. Hypothesis Seven (H7), that there will be a significant difference between experiences in involvement in the AIS (number of years) and readiness to implement data mining is supported.

6.2.8 Data mining readiness and utilisation groups

Respondents were asked to indicate their readiness toward adopting data mining technology regardless as to whether they were already using such technology. It was believed that there would be different level of readiness among different groups of respondent dependent on whether they were currently adopting data mining, not adopting it or not aware of the technology. Those respondents currently adopting such technology would be expected to have higher levels of readiness toward acceptance than for those who not aware or those who not adopting it.

Hypothesis Eight

H8: There is a significant difference between adopter, non-adopter and don't know (not aware) groups in their readiness towards data mining technology.

To assess utilisation respondents were asked whether their departments used data mining technology. Responses were categorised as adopter (Yes, use data mining tools), non-adopter (No, never use data mining tools), or Don't Know/Not Aware (Have no knowledge of the use of such tools by the department).

The mean scores (Table 6.26) indicate that the adopters of data mining technology reflect the highest readiness score (4.16) as compared to the other groups. This is not unexpected as it would be expected that these groups have given greater thought to the adoption of technology than the other groups. Interestingly, the non-adopter also scored relatively high readiness toward data mining technology (mean 3.89). This suggests, although their department or unit within the department were not using such technology, they also have a high readiness toward such technology. For those who don't know or were not aware whether their department had adopted such technology or not, have also scored a positive mean score (mean 3.98). This reflected that overall all respondents were ready to adopt data mining regardless of awareness about it current utilisation of such technology. There are minimal differences in mean scores between three groups identified. ANOVA was adopted to investigate whether the differences in means were significant. Table 6.26 summarized the results of this analysis.

Table 6.26: ANOVA: Data mining readiness vs. utilisation

Utilisation group	n	Mean	Std. Deviation	ANOVA F	ANOVA Sig.
Adopter	25	4.1640	.47511	1.950	.146
Non-adopter	25	3.8960	.56309		
Don't Know/ Not Aware	82	3.9780	.48990		

The result indicates that the difference between the three groups is not significant. This suggests that there is no significant difference between readiness to implement and the utilisation of data mining technology among adopter, non-adopter and don't know groups. F value of 1.950 is not significant (p=0.146), which is greater than minimum requirement for statistical significance (0.05). Therefore, Hypothesis Eight (H8) that there is a significant difference between adopter, non-adopter and don't know/not aware groups in their readiness towards data mining technology is not substantiated.

6.2.9 Knowledge about data mining and perception of data mining impact

Respondents were requested to rank their knowledge about data mining and their perception of the impact data mining could have on the performance of the AIS and decision making process. The intention is to assess whether different levels of knowledge about data mining would be reflected in different perceptions by respondents of the impact data mining could have on AIS and on decision making. It is expected that those responses with higher knowledge would have higher expectation and perception of data mining impact toward performance and decision making. Therefore, Hypotheses Nine (H9) was posed:

H9.1: Respondents with a greater knowledge of data mining technology have a higher perception or expectation of the impact of data mining on the AIS than those with less.

H9.2: Respondents with a greater knowledge of data mining technology have a higher perception or expectation of the impact of data mining on decision making process than those with less.

These hypotheses were tested by applying ANOVA.

Table 6.27: ANOVA: Data Mining knowledge vs. perception of data mining impacts

Variables		n	Mean	Std. Deviation	ANOVA F	ANOVA Sig
PImpctAIS	No knowledge	24	3.5833	.55613	4.918	.003
	Little knowledge	48	4.0000	.47580		
	Average knowledge	53	4.0038	.52549		
	Good knowledge	10	4.1800	.62858		
PImpctDecM	No knowledge	24	3.5139	.50101	9.541	.000
	Little knowledge	48	4.1528	.54125		
	Average knowledge	53	4.1384	.54473		
	Good knowledge	10	4.3000	.63732		

The results (Table 6.27) show that there is a significant different between the level of knowledge and perception of the impact of data mining on the performance of the AIS ($F(3,131)=4.918$, p=.003) and their perception of impact of data mining on decision making ($F(3,131)=9.541$, p=.000).

Further analysis adopting a post hoc test are intended to indicate where the differences are actually happen among different rank of knowledge about data mining. Respondents (Table 6.27) with a good knowledge of data mining have higher means of their perception on both issues while group with no knowledge have the lowest perception of the both impact of data mining. This might be expected as their limited knowledge would in all probability affect their perception of the impact of such technology.

Results shown in Table 6.28, indicates that the group with no knowledge is significantly different from those with knowledge and reflecting that officers with little to good knowledge about data mining have a greater perception of the likely impact of data mining technology.

Table 6.28: Tukey post-hoc test: Perception of impact and level of data mining knowledge

Dependent Variable	(I) Rank of knowledge about data mining	(J) Rank of knowledge about data mining	Mean Difference (I-J)	Sig.
PImpctAIS	No knowledge	Little knowledge	-.41667(*)	**.009**
		Average knowledge	-.42044(*)	**.007**
		Good knowledge	-.59667(*)	**.015**
	Little knowledge	No knowledge	.41667(*)	.009
		Average knowledge	-.00377	1.000
		Good knowledge	-.18000	.754
	Average knowledge	No knowledge	.42044(*)	.007
		Little knowledge	.00377	1.000
		Good knowledge	-.17623	.761
	Good knowledge	No knowledge	.59667(*)	.015
		Little knowledge	.18000	.754
		Average knowledge	.17623	.761
PImpctDecM	No knowledge	Little knowledge	-.63889(*)	**.000**
		Average knowledge	-.62448(*)	**.000**
		Good knowledge	-.78611(*)	**.001**
	Little knowledge	No knowledge	.63889(*)	.000
		Average knowledge	.01441	.999
		Good knowledge	-.14722	.863
	Average knowledge	No knowledge	.62448(*)	.000
		Little knowledge	-.01441	.999
		Good knowledge	-.16164	.824
	Good knowledge	No knowledge	.78611(*)	.001
		Little knowledge	.14722	.863
		Average knowledge	.16164	.824

Within groups of officers with knowledge however, (although mean shows some differences) there is no significant different between them. It can be concluded that there is no difference in perception between respondents with little knowledge, average knowledge and good knowledge. Therefore, both hypotheses (H9.1 and H9.2) are partly supported that suggests there is a significant difference between the group with no knowledge and the groups with knowledge about data mining.

6.2.10 Ability to utilise data mining and performance of the AIS

In this section, Hypothesis Ten (H10) was posed to consider the whether there was a relationship between the ability to utilise data mining technology and the actual performance of the AIS.

Hypothesis Ten

H10: There is a relationship between ability to utilise data mining and the performance of Accounting Information System.

The performance of AIS was measured through respondents' satisfactions and their assessment on its overall data quality the systems produce. It includes accuracy, up to date, completeness and consistencies of data. Apart from its data quality, other factors which important in assessing the performance of AIS were also being investigated in the questionnaires[45]. An ability to utilise data mining technology was suggests as one of the variable in the assessment of AIS performance it the questionnaire. In attempt to test this hypothesis, a correlation analysis was adopted.

A correlation analysis of the two variables, which are: AIS performance and ability to utilise data mining, revealed significant correlations between them $r(128)=.229$, $p=.009$. However, since 0.229 is not relatively close to 1 or -1 (as SPSS measure the strength of association), it was indicates that ability to utilise data mining and performance of AIS are not strongly correlated.

In conclusion, there is only a weak relationship between ability to utilise data mining tools and performance of AIS. However, Hypothesis Ten (H10) that, there is a relationship between ability to utilise data mining with the performance of Accounting Information System is supported. It does suggest that an ability to utilise this technology within the department would have contributed to the increased performance of the Accounting Information System.

[45] Refer section 1.5 in the Questionnaire-Refer Appendix One (1.2)

This study explored the utilisation of data mining within the Accounting Information System (AIS) in the public sector within Malaysia. One of the objectives of this study was to develop a data mining utilisation model. This model is now discussed.

6.3 Proposed Data Mining Model

The final research question posed was:

'What model would allow the Malaysian public sector to best apply data mining techniques to ensure high quality information within the accounting information systems?'

At the present time the public sector's accounting information system centered on the use of Branch Accounting System, Payroll Systems, Central Information System, Investment and Loan System, Subsidiary Ledger Accounting System and, Financial and Management Accounting System. With these systems, the Central Information System (CIS) is treated as a central data repository for any further activities. Reports are prepared from it, and disseminated to the statistics department, self accounting department (SAD), program monitoring system (SETIA) and treasury. Other systems related this such as *e-spkb* is used by many departments to control budgets and expenditures which are also linked to head quarters of the Accountant General's Department.

As found in this study, forty percent of respondents recognised that the systems required improvement. The current move to a new Government Financial and Management Accounting System (GFMAS)[46] is viewed as an approach to improving the accounting system. With this new system, a data warehouse was established called the Business Warehouse (BW). This data warehouse represents the central data

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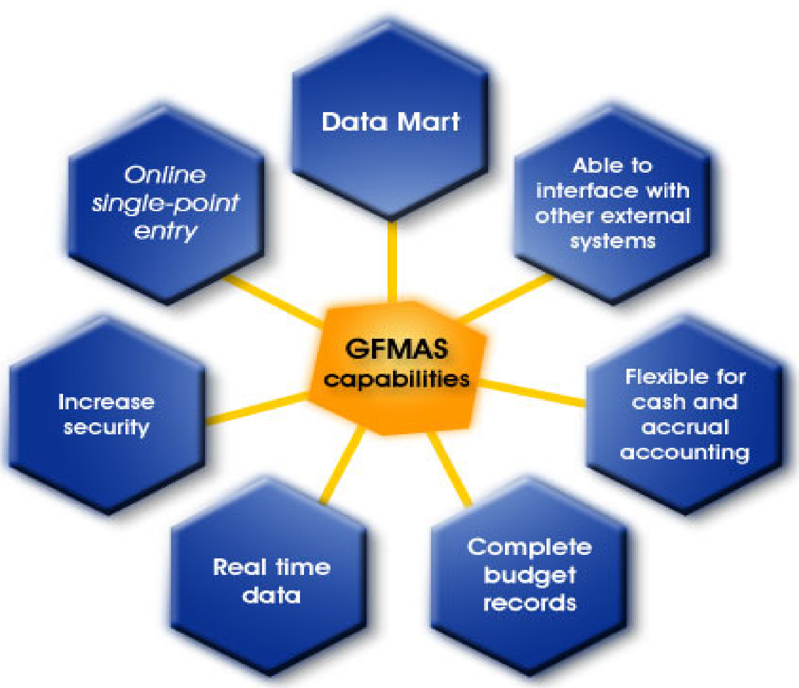
[46] **GFMAS** is an integrated system which is capable of allowing acceleration in financial planning, budget control and government accounting. It combines all the accounting functions that cover payment, receipts, remuneration control, unclaimed monies, government loans, loans and advance payment to public sector personnel, investment and preparation of the Public Accounts in one integrated platform. It commenced on 2006(www.anm.gov.my)

repository for the public sector accounting systems manage by Accountant General's Department. The initiative to move from older system to a new GFMAS is an attempt to improve the accounting and financial management in the public sector's departments. At the same time, this move is also seen to be an attempt to increase the quality of data produced and the performance of the accounting systems.

As shown in figure 6.1, GFMAS has the ability to provide an online single-point entry, increase security, real time data, and completeness of budget records. It also has the capability to be use for cash basis accounting and accrual based accounting. It is also able to interface with external systems and created its own data mart. This is where data mining technologies, on request for access to data, can then play a roles in analysing, interrogate, or mining the data for the decision making processes. Data mining has many potential uses in accounting in the public sector, it can assist in dealing with the government's payment to suppliers, and government expenditures on assets for example in monitoring and detecting any unauthorized payments on assets. It would increase a department's efficiencies and effectiveness in their operations and enhance their accountability.

Figure 6.1: GFMAS capabilities



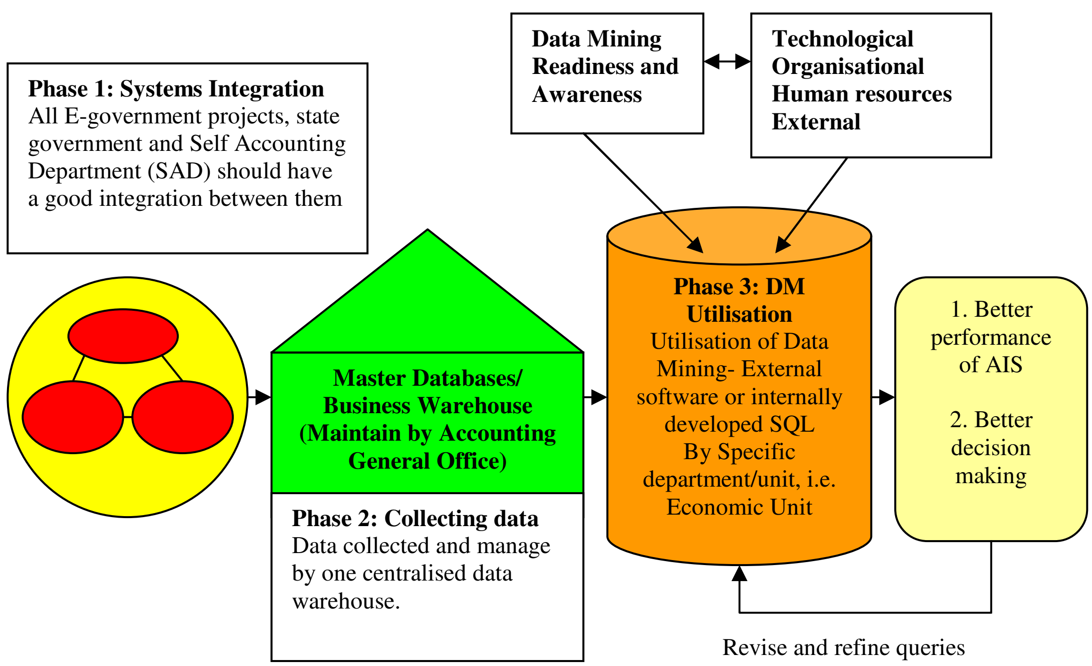
A part of this study is to identify a model that would offer advice on the best approach to implement data mining technology into the accounting information system within the public sector in Malaysia. Fundamental to this model is the need to set in place a warehouse to manage data effectively, given the number of public sector departments using data, and often of the same type. A central data composite would seem most practical. This new system 'Government Financial Management Accounting System (GFMAS)' enables the provision of a master database through a Business Warehouse (BW) and data marts. The application of data mining technologies within this system would seem appropriate. With this data warehouse, it would be easier to utilise and implement further data mining techniques. The adoption of this new accounting system has created a good foundation for the utilisation of data mining technology.

6.3.1 The proposed model of data mining utilisation (DMU)

The identification of an appropriate data mining model for use in the public sector in Malaysia would seem timely given the current situation where there is little implementation of data mining technology in this sector and there are high levels of readiness toward adopting such technology indicated. Additionally this is supported by the adoption by the government of a new accounting system providing a good foundation for the adoption of data mining techniques within the accounting information system. Subsequent discussion proposes a best practice model of data mining utilisation within the accounting information system in Malaysia.

The model proposed consists of three phases which includes integration of systems, collection of data and analysis (data mining) activities (See Figure 7.3). First and foremost, in attempting to apply data mining technologies, a good interaction between all public sector accounting systems has to be achieved. As suggested from the interview findings, a problem with integration of systems is the first component which needs to be dealt before progressing to any other data analysis projects. This suggest that issues of integration of the various accounting system is primarily important in ensuring the data collected were complete, accurate, up to date and consistent. As discussed earlier, GFMAS was designed to have the capability to integrate with an external system. A good integration between various systems will enable data to be shared between departments with fewer problems in terms of formats and issues of timeliness. This is because, while maintaining and retaining the ownerships of the data, a good integration will provide a timely data from it sources. It will also reduce the possibility of inconsistencies in data between difference agencies and departments. To some extent, GFMAS has provide the ability to integrate, however since the system is newly implemented (early 2006), interviews comments showed a dissatisfaction with its integration capability. The proposed model stresses the integration of public sector systems especially all electronic government projects, state government and also Self Accounting Department (SAD) in order to create one centralised data warehouse where better management of data can take place. It can improve data sharing, controlled flow of information, reduce duplication, and increase the quality of data used in the decision making process.

Figure 6.2 Public sector data mining utilisation model



A Business Warehouse (BW) within GFMAS would enable the accounting department to become a central repository and take custodial responsibility of all accounting and finance information for the public sector in Malaysia. From this central repository all departments would be enabled to access the data base and undertake data mining activities to support their decisions. At the same time, internal control, the security of data, its reliability and also its accuracy need to be scrutinized to ensure that there is good quality data for the next phase. The use of such a central repository will assist in mitigating the problem of time wastage in conducting further analysis in a more fragmented environment. The value of storing large, accessible amounts of data will depend on the ability of public sector staff to extract useful reports, identify interesting events and trends, identify how the data can be used to support decision making and policy development, undertake statistical analysis and derive inferences, and also exploit the data to achieve departments, ministries and government goals. This study has shown that the basic foundation for data mining utilisation is in place as a result of the implementation of a new information system (GFMAS). Two phases identified in developing a best practice model identified the importance of system integration and the creation of a centralised accounting data warehouse.

Before moving to the final phase of the actual implementation of data mining tools, issues such as awareness, readiness of staff and the four contextual issues technological, organisational and human resources and external factors must be considered. Organisational issues such as full commitment and support from top management are important in supporting the technological issues. Such support assists in enabling any projects planned by the organisation including data mining utilisation to be successful. In the public sector organisation, support from politician such as minister can play an important role in the utilisation of technology.

Human resource is a major consideration in data mining projects. It is important for the public sector department to have an effective and adequate training for staff to increase awareness and also acceptance toward new technology such as data mining. Therefore, continuous awareness programs through seminars and hands-on training is vital. Through these programs and training, staff are exposed to data mining technology and enabled to develop their skills and understanding. The awareness programs will also increase the level of readiness toward such technology. As found in this study, there is encouraging level of readiness toward data mining technology, therefore a combination and consideration of four issues in the policies and working procedures will further enhance the successful of data mining utilisation within their accounting system in the public sector.

The final stage of the proposed model is crucial where the actual utilisation of data mining tools is applied to the analysis of accounting data available for the various purposes of the departments. In any decision making activities within the public sector firm and solid support from available data and reports is vital. Data mining activities will assist in ensuring the quality reports are produced. The findings in this thesis support this view suggesting the application of such tools will increase the capability of public sector staff to produce better reports which should result in better decision making. Reports can be supported with features such as graphs, charts, forecasts, and fraud detection reports enhancing the opportunity for effectiveness decision making within the public sector departments.

At the present time, for those who indicated that they adopted data mining tools, the data to be mined are requested from the accounting department and this data will be stored on the data miner's PCs and then data mining activities are undertaken locally. Applying the approach identified in this thesis, utilising the new GFMAS system a central data warehouse is created and data mining activities would be undertaken from this central warehouse creating accessibility for all departments and providing an integration of PCs throughout the public sector linked directly to this data warehouse and creating the capability of running data mining activities. However, there would need to be a policy relating to access to the data warehouse which would need to be developed by the accounting department. As found from this study, a specific department or unit should be appointed to have full access and undertake all data mining activities on behalf of the government. For example, the Auditor General Office or Economic Planning Unit might have a full access to such data warehouse. There are potential privacy concerns and risks of misuse of information that would need to be addressed. Access levels would need to be imposed dependent on the data needs of each department, and this should assist in reducing privacy and information misuse risks. With such policies and controls in place the security, reliability and accountability of departments should be enhanced.

6.4 Conclusion

In this chapter, statistical results for testing the hypotheses for the study were presented. In the case of influence factors in the decision to utilise data mining, organisational, technological, and human resources issues were important and affect the decision to utilise data mining technology. While for those who not utilise the technology, issues relating to technological, organisational and human resources were the reasons identified for their decision not to utilise such technology. The intention to utilise data mining technology was found to have a relationship with the knowledge respondent had about it. In terms of readiness toward adopting data mining, there was no difference found between gender, job functions, or groups of adopters to accept data mining technologies in the future. However, the level of education and experience in Accounting Information System was found to influence readiness to adopt. Knowledge about data mining will affects expectations of the impact data mining could have on the Accounting Information System and decision making. The performance of Accounting Information System is found to have a correlation with the ability to utilise data mining within the public sector.

Chapter 7

Conclusions, Limitations and Future Research

7.1 Introduction

The importance and role of technology within the business environment has grown exponentially in recent years. Issues of concern have been raised and investigated by researchers. For example, relationships between information technology and organisational change agility (Carlson, 1999, Zain *et al.,* 2004), understanding the reasons for the adoption of technology (Spanos *et al.,* 2002, Rienenschneider *et al.,* 2003) and individual characteristics which are likely to result in a favourable environment for the adoption of technology (Agarwal & Prasad, 1999, Venkatesh & Morris, 2000). Accountancy has inevitably been associated with technological development and advancement (Schlageter, 2005). Studies incorporating information technology and influences on user decisions in various perspectives including accounting has been investigated (Benford & Hunton, 1999, O'Donnell & David, 2000). Data mining is one of the many technologies which is increasingly popular as a strategic business tool within financial institution, accounting and auditing (Vojinovic *et al.,* 2001, Kloptchenko *et al.,* 2004, Dahlan *et al.,* 2002, Lampe & Garcia, 2004).

In the light of changes in technology and its use in the business environment it would seem to be crucial that data mining technologies be adopted within the public sector. The application of technology, in particular data mining technology in the accounting information system within the public sector in Malaysia is addressed in this study. Data mining within the Accounting Information Systems is identified as the *'the process of collecting, collating and thoroughly analysing accounting data for presentation in a format allowing the generation of information and the creation of knowledge through the analysis of this information to enhance the decision-making process within the public sector organisation.'* It adopts an updated data analysis approach via a variety of technological techniques and tools to explore (summaries, comparison, analysis, forecast, estimate) the accounting data within the accounting department(s) in the public sector.

The major research problem addressed within this study was an investigation of the lack of knowledge of the status of both the awareness and the implementation of data mining technology within the accounting information systems in the Malaysian public sector and the benefits to be derived by implementing such technologies. The study sought to increase our understanding of the extent data mining technology is being utilised, and implemented and whether, where data mining technology is not implemented, there are plans to implement within the Malaysian public sector. Areas of interest for this study have been the departmental awareness and readiness toward accepting data mining technology, the factors influencing and the reasons for utilising or not utilising this technology, the impact of data mining technology, identifying criteria by which to evaluate the performance of the AIS, and the best potential model of data mining utilisation within the public sector.

An awareness and readiness to implement t data mining technology is the most important criteria for the successful implementation of technology within an organisation. For example, in organisations such as banks, financial institutional and insurance industries, many studies have investigated awareness and readiness to implement (Berger, 1999, Dahlan *et al.,* 2002, Chye & Gerry, 2002, Chun & Kim, 2004). Technology is commonly adopted by organisations dealing with large amounts of data such as in the banking and finance sector. However, this has not been the case in the public sector. In the public sector there has been little pressure to follow the trend of private sector. However good governance in the management of data will always be important regardless of whether it is public or private. A range of issues were considered in addition to awareness and readiness, these included, technological, organisational characteristics, human resource and external issues and were found to play an important role in the implementation of technology. These broad issues were found to affect the organisation's decision to utilise or not to utilise such technology.

Technology utilisation will be influenced by the organisations perception of the benefits that are likely to flow from the adoption of technology. From the perspective of the decision making process various technological approaches have been studied seeking to identify how the implementation of technology affects and supports the decision making process, and assists in improving the quality of decisions (Bots & Lootsma, 2000, Poston & Grabski, 2001, Kloptchenko *et al.,* 2004). In this study data mining utilisation within the Accounting Information System (AIS) was investigated to assess its perceived impact on the performance of accounting information system and the decision making process.

The successful implementation of data mining technology must be associated with proper planning, modelling and the development of an implementation strategy. In the case of the utilisation of data mining within the public sector optimum benefits will only be reaped if an appropriate proper model for implementation is identified. This study identifies a best practice model to be applied in the context of Malaysian public sector.

7.2 Summary of Hypothesis testing

The study set out to investigate a number of research questions and objectives that the research was to fulfil. Utilisation of data mining was found to be central to the framework indicating that technological, organisational, human resources and external issue were important in the decision as whether to adopt or not to adopt the technology. Readiness toward data mining technology which measured through optimism, innovativeness, perceive usefulness and perceive ease to use, contributes to the strong intention to adopt data mining technology. Individual differences in regards to readiness has provides a greater understanding in regard to characteristics of respondents. Knowledge and awareness was also found to be associated with the willingness and intention to utilise such technology. The utilisation of data mining was found to have a significant impact on the creating a better performance of the accounting information system and also improving the process of decision making.

Technological, organisational, human resource and external issues were found to be significant factors (H1) in the decision to adopt and utilise data mining. Technological, organisational and human resources were also found to be significant reasons (H2) for those who choose not to utilise data mining. Other findings from the qualitative data, indicate that good infrastructure, on going training, workshop and other awareness programs in developing human capital would assist in ensuring the successful implementation of new technology including a data mining technologies. It is a challenge to the public sector to successfully implement any new technology since it will involve many levels of implementation and various issues need to be considered for example in attempt to increase staff's awareness and capability dealing with new innovations of technology. Continuous programs with interactive features of hand-on training besides some other strategy would be good to be considered. This is because human capital seen to be the most important factor in any technological implementation projects.

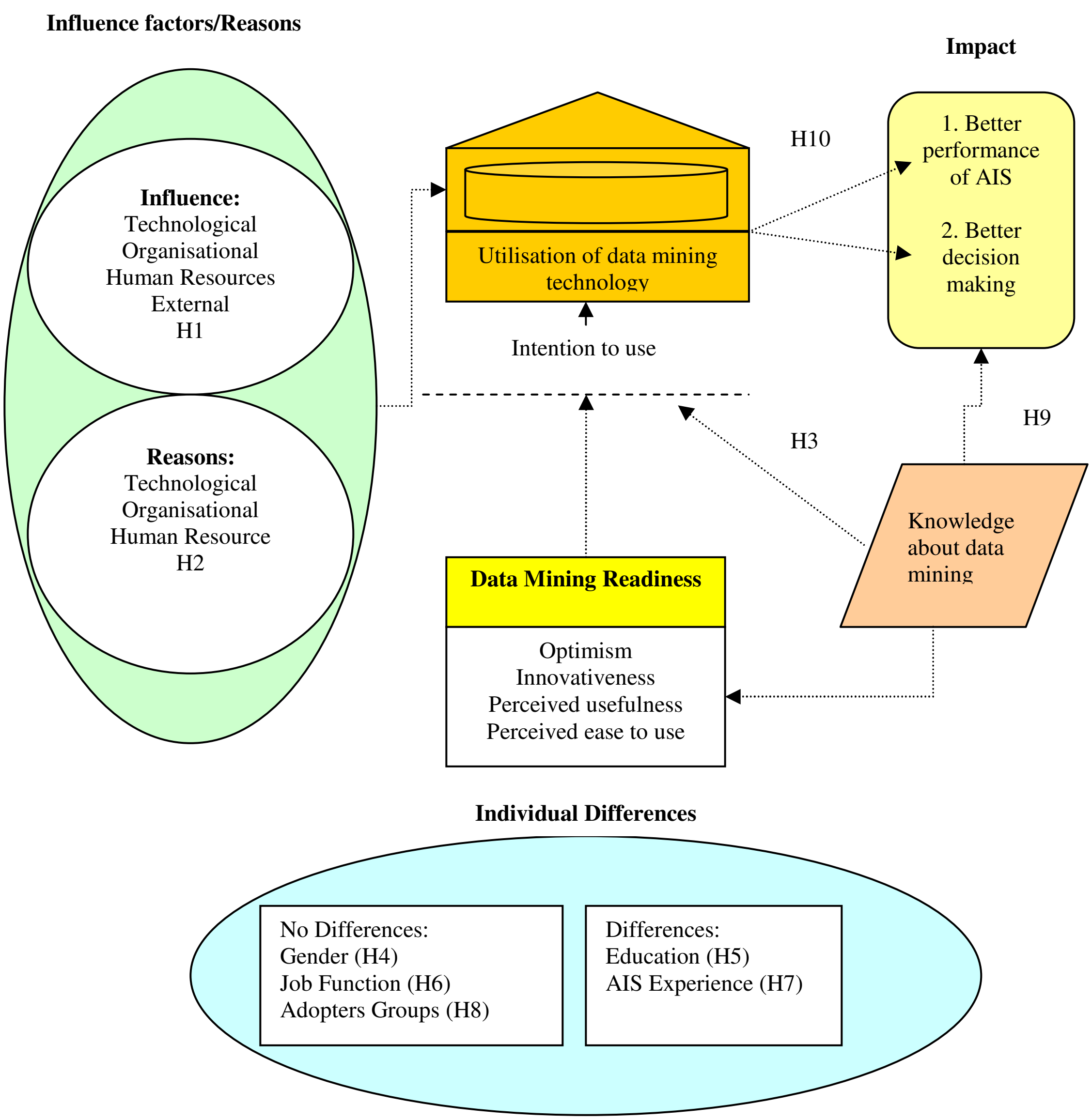
The data has revealed that the public sector does have good programs in implementing technology utilisation within departments with courses, hand-on training and awareness programs. Awareness and knowledge about such technology was found to be correlated with the intention to use data mining technology (H3). These programs have to be concurrently brought together with good leadership which reflects the views that top management are one of the major factors in rolling out a good implementation of any technology. From the survey and the interviews, it appears that top management are generally very supportive of technology developments. All public sector staff for example are required to attend professional development courses for at least 7 days per year to develop a range of skills including the use of technology. This policy reflects the concern of the Malaysian Prime Minister on the need to enhance human capital, the development of technological skills being one of them.

Although data mining technology was not widely adopted, the readiness and level of intention to adopt reflects a strong indication that the adoption of this technology is favored. Results indicated high levels of optimism, innovativeness and perceptions of ease of use, and usefulness towards data mining technology. It also has confirmed that optimism and innovativeness are the key drivers to data mining readiness which was also found by Dahlan *et al.,* (2002). In the process of developing a model for this study a combination of Dahlan's *et al.,* (2002) data mining readiness framework and elements of the Technology Acceptance Model (TAM) were adopted to measure technological readiness. These two models were found to offer a good foundation from which to develop a new perspective on measuring readiness among workers or public servants towards the adoption of new technology. Further analysis on readiness, the study found that differences in gender, job function and utilisation groups make no difference in the readiness of public sector department staff toward this technology (H4, H6 and H8). However, experience in the Accounting Information System (AIS), and the level of education are reflected in different levels of readiness toward the adoption of data mining technology (H5 and H7).

The summary shown in Figure 7.1 both summarises and demonstrates the interaction between the variables that were investigated in this study. This summary draws together each of the hypotheses demonstrating how they have been used to achieve the objectives of this study and offer insights into the utilization of, and attitudes toward data mining in the Malaysian public sector.

Figure 7.1

Framework for understanding the relationships between variables in the utilisation of data mining[47]



Identified within the thesis factors that influence the decision to utilize data mining technology were discussed. These were discussed as technological, organizational, human resource and external influences, and technological, organizational, and human resource reasons. Readiness to implement data mining technology was

[47] 'H' refers to each hypothesis tested.

discussed in terms of knowledge possessed regarding sata mining. Readiness was investigated in the context of optimism, innovativeness, perceived usefulness and perceptions of ease of use. Knowledge and the decision to utilize was recognized as influencing impact in terms of better AIS performance and improved decision making capability. Testing was also undertaken for individual differences – whether differences in gender, job function, adopter versus non adopter, education levels and experience utilizing the AIS.

Most of the respondents indicated their departments did not have any specific data mining software but did have a positive view in accepting it, and utilising it in the future. Knowledge and awareness about data mining plays a role in shaping perception and behaviour of officers and staff. The study found that limited knowledge is associated with lower expectations of the impact data mining could have on their accounting systems and the decision making process (H9). Departments using data mining technology would appear to have better accounting knowledge and be in a position to make better financial decisions. The study has found that the ability to utilise data mining would have an impact to the performance of accounting information systems (H10).

7.3 Proposed data mining model

The adoption of data mining techniques has become increasingly popular among organisations especially within the both private sector and public sector in areas such as marketing, finance, banking, manufacturing, medicine, process control, telecommunications (Brachman *et al.,* 1996, Olaru, 1999, Thuraisingham, 2000, Chan & Lewis, 2002, Rafalski, 2002, Smith, 2002), accounting, auditing for government's project and programs (Carbone, 1998, Kostoff & Geisler, 1999, Weber, 2002, GAO, 2003).

As in the private sector the public sector is finding a number of practical issues need to be resolved in the development of approaches to the utilisation of data mining techniques including insufficient training, inadequate data mining tool support, data unavailability, and complexity of data types (Brachman *et al.,* 1996). However, the results of this study identified the potential benefits of applying data mining technology in the public sector as has occurred in the private sector. Use of it is related to public sector activities which increasingly relying on technology in regard to project monitoring, E-government projects, taxation, fraud detection and general auditing. Data mining technology offers the opportunity to the public sector to put in place better controls to assist in public fund management and offer a means for accountability to be demonstrated by public sector departments.

In terms of specific data mining tools, there is a choice in that both independent software and in-built capability can be used. As found in this study, currently, independent software is commonly adopted for use in data mining activities. It may be best to use this independent software for the departmental level of data mining activities which also called DM offline software structure (Olaru, 1999). There are suggestions on the development of internal capability of current data warehouse to undertake data mining activities. This internally built structure of data mining able to handle larger amount of data as compared to independent software. It also called DM in place software structure (Olaru, 1999). Whatever approach is adopted the software adopted should be capable of use for various purposes at different levels, be easy to use and to understand, to upgradeable and cost efficient. The adoption and utilisation of data mining technology will then increase the performance of Accounting Information System (AIS) and also the process of decision making.

7.4 Contributions

In this study, a Data Mining Utilisation (DMU) research model has been developed to allow a better understanding of the status of utilisation, influential factors, reasons, awareness of the concepts, readiness to adopt and utilise data mining technology and the impact of data mining in the context of Malaysian public sector. All these issues have been investigated and discussed. The literature review revealed that there was a lack of research on the utilisation of data mining in the public sector especially in the accounting area. The results of this study contribute the following:

1. By providing insight into the state of adoption and utilisation of technology (i.e. data mining technology) in the accounting information system in the public sector in Malaysia.
2. By providing insight to the important issues should be taken into consideration in the implementation of data mining in the public sector in Malaysia.
3. By measuring the level of awareness readiness toward accepting data mining technology amongst public sector employees.
4. By providing insights into respondent attitudes toward perception of impact of data mining technology.
5. By developing a model to be adopted in the successful implementation of data mining technology within the Accounting Information System (AIS).

Redevelopment of the readiness construct (from TRI, TAM and DMR)[48] has proved to be a good measure applied to this study. It supports the findings from previous studies in identifying optimism and innovativeness as enablers to technological readiness. The other two beliefs (perceived ease to use and perceived usefulness) also contributed to the constructs which were found to be successful measures reflecting the intention to adopt technology amongst respondents. The findings in both phases (quantitative and qualitative) of this study contribute to the literature of acceptance and readiness toward data mining technology within public sector organisations. They support the view that these constructs are suited to the public sector as well as the private sector. This is primarily because, the construct measure the level of optimism, innovativeness, perceived ease of use and perceived usefulness does not restrict to the environment surrounding but rather to the beliefs and perception one has of a particular thing, in this case technological tools.

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[48] Technology Readiness Index (TRI) Parasuraman (2000)
Technology Acceptance Model (TAM) Legris *et al.,* (2003), Riemenshchneider *et al.,* (2003), Amoako-Gyampah & Salam (2004)
Data Mining Readiness Framework (DMR) Dahlan *et al.*,(2002)

Identification of the impact of data mining and the important criteria in gauging the performance of the AIS contributes to the body of knowledge both in AIS and data analysis technology. For example, the importance of data quality has been noted by many researchers (see Kaplan *et al.,* 1998, Dahlan *et al.,* 2002, Ikart, 2005). This study, has show that better quality data and information can be accessed by utilising data mining resulting in a more efficient accounting information systems and assist in more effective decision making.

This study contributes by offering insights into departments' top management, accountants, auditors, ICT personnel and academicians as well to obtain a better understanding of the issues of the adoption of data mining technology within the of accounting information systems.

7.5 Limitations

The study was constrained to departments within the public sector and to one country, Malaysia. However, there is some evidence suggesting differences between the information needs of the accounting and finance department and other public sector departments are likely to be minor. In addition to that, each government department reflects the policies and regulations set by the government and would have similar or same implication for all departments.

Although a thirty nine percent response rate is acceptable for survey research, more meaningful statistical tests would be available if the response rate was higher and embraced more departments. A number of strategies were implemented to boost the response rate. Emails, approval letter (with research card) from the department of the Prime Minister, an approval letter from head of department, assistance from senior officers in distributing and collecting questionnaires were not sufficient to encourage a higher response rate from public servants. There have been similar concerns raised with other research approaching similar types of respondent for example Ang *et al.,* 2001 obtained 38% of usable observation of response rate. Perhaps, in the future researchers can offer either incentive for all respondents or attractive prizes for early respondents for example. The adoption of a qualitative phase assisted in addressing these concerns. The results and implications for this study may have been enhanced if the number of interviewees had been expanded.

7.6 Further research opportunities

The first recommendation would be a replication of this study in different settings which might include public sector departments in other countries to provide interesting insights into national comparisons and international practices. Research on cross-country and cross culture comparisons of the level of readiness, the model utilised, and the impact of such utilisation on decision making.

Secondly, research on the perception of accountants compared with the perceptions of auditors toward technology may offer interesting insights into the identification of underlying factors or perhaps reconfirming the notion that job functions would have moulded their perception toward technology within working environment.

Since, there is strong interest in adopting such technology, a longitudinal study may be useful to provide further insights into public sector efforts and whether these actually lead to a better performance and public accountability. For example, longitudinal approach with data gathered from more organisations across various ministries in achieving objective for instance, understanding gender differences over the long term as it relates to sustained usage of data mining with increasing experiences.

Finally, research discussing political influences in the public sector would interesting. It is true that, the public sector should to be seen as non-partisan, however incumbent political situations seem to have an influence on the government's decision.

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Appendix One: Covering Letter and Questionnaire

Appendix 1.1 (Questionnaires cover letter)

UNIVERSITY OF TASMANIA
School of Accounting and Finance

«FirstName» «LastName»
«JobTitle»
«Department»
«Address1»
«Address2» «City»
«State» «PostalCode»

<Date>

Dear «FirstName»

My name is Mohd Shaari Abd Rahman and I am currently enrolled in a Doctoral degree in Accounting at the University of Tasmania under the supervision of Dr Trevor Wilmshurst. I am conducting research into the utilisation of Data Mining Technologies within the Accounting Information System in the Public Sector – A Country Study – Malaysia. Basically, the study aims to investigate and explore current status of utilisation of this technology and examine the potential development of an effective model of data mining within the accounting information systems in Malaysian public sector. This study is important in view of gaps in the literature and the lack of knowledge about data mining technology within accounting information system environment in the public sector organisations. It is important to discover such knowledge as it could give an indication whether or not this technology can assist the government sector in enhancing the integrity of its management.

Primarily, the study aims to investigate the status of data mining technology implementation within the accounting information system in the Malaysian public sector. This information may be of benefit to your organisation since it could help its management, accountants and ICT personnel to better understand the issues of new technology, such as data mining, within the area of accounting information systems. It may also assist in assessing whether this new technology can provide better foundation for better information and effective decisions.

The purpose of this letter is to enquire as to the possibility of your organisation being one of the participants for the mail survey. For your information, departments and statutory bodies under Ministry of Finance and one department under Prime Minister's Office have been selected for participation in this survey. Since the study investigates data mining in relation to the Accounting Information System (AIS), and a major function of your department in accounting and finance decision-making, your participation in the survey is felt to be important. This mail survey is crucial part of my study, which will improve the richness of the quality of the results within this study. Views and opinion from your organisation would be very important to this research. Therefore, your reply to the attached questionnaire would be greatly appreciated. It is envisaged that this mail survey would take approximately 15 - 25 minutes to complete.

Please note that the actual survey instrument does not request any identifying details, and so your responses will not be identifiable in my thesis or any other research output from the study. In any case, the data from the completed surveys will be reported in an aggregated form, so there is no possibility that you or your organisation will be identifiable.

Your name is, however, requested *on a separate sheet* but *only if you wish to be involved in the second stage of this study*, namely an interview to investigate the themes arising out of the completed surveys. If you express an interest in participating in an interview, the separate sheet containing your details will not be linked to your survey responses, and will be stored separately from those responses. You will then be sent a separate information sheet explaining the interview stage, at which time you will be able to decide whether or not you wish to be interviewed. In any event, no attempt will be made to identify your organisation, even if possible, in any published material. All raw data collected from this study will be securely stored at the School of Accounting and Finance for a period of five years. At the expiry of this five year period, the data will be destroyed. I would be happy to give you a summary of my findings once my thesis is completed. Simply email me and I will arrange this.

This study has been approved by the Human Research Ethics Committee (Tasmania) Network. If you have any concerns of an ethical nature or complaints about the nature in which the project is conducted, you may contact the Executive Officer of the Human Research Ethics Committee (Tasmania) Network.

Executive Officer:	Amanda McAully
Email:	Amanda.McAully@utas.edu.au
Phone:	61 3 62262763
Fax:	61 3 62267148

Please understand that your participation is entirely voluntary and evidenced by returning the completed survey. Of course, your participation would be appreciated and I look forward to receiving your completed questionnaire by the end of January 2006.

Should you have any queries regarding the project or questionnaire, please feel free to contact me on +61 (03) 62262801 or e-mail:msabd@utas.edu.au or my principal supervisor, Dr. Trevor Wilmshurst on email:Trevor.Wilmshurst@utas.edu.au. Your reply can be returned to my collection base in Fakulti Pengurusan dan Ekonomi, Kolej Universiti Sains dan Teknologi Malaysia (KUSTEM), Mengabang Telipot 21030 Kuala Terengganu, Malaysia in the prepaid envelope supplied.

I look forward to hearing from you.

Your sincerely,

Mohd Shaari Abd Rahman
PhD Candidate
Student ID 039115
School of Accounting and Finance
University of Tasmania

Co-signed:

Dr Trevor Wilmshurst
Senior Lecturer
Acting Head of School
Research Higher Degrees Co-Ordinator
School of Accounting and Finance
University of Tasmania

Appendix 1.2: Mail questionnaires

UNIVERSITY OF TASMANIA

School of Accounting and Finance

QUESTIONNAIRE

The Utilisation of Data Mining Technologies within the Accounting Information System in the Public Sector – A Country Study - Malaysia

Directions: This questionnaire is presented in five sections; the first section seeks basic information about your accounting systems and your perception on its performance. Second and third section is relates to data mining readiness and the implementation. Section four investigates the perception on impact of data mining on your accounting system and decision process. And finally, section five seeks basic information about your background within organisation.

Note: There are two versions of questionnaire (*English* and *Bahasa Malaysia*), choose either one to answer.

Your assistance is greatly appreciated.

To assist you in responding to this questionnaire a number of terms used are defined to ensure you understand how I am using these terms in this study.

Accounting Information System (AIS) is a term which describes the financial recording system implemented by your organisation and consists of subsystems such as transaction processing system, general ledger/financial reporting system, fixed asset systems and management reporting system.
Data mining is the processes of analyzing the data in a value adding process to generate information and knowledge (pattern and relationships) to enhance the decision-making processes within the organisation. It uses an updated data analysis via a variety of techniques and tools to explore (summaries, comparison, analysis, forecast, estimate) the data.
Data Mining tools: Software, which used to find patterns and regularities in sets of data (for example, Clementine, Enterprise Miner, Intelligent Miner, Darwin, Scenario, Knowledge SEEKER, DataMind Data Cruncher).
Adopters of Data Mining: Organisations that have implemented data mining tools or currently implementing any data mining software.

1: Accounting Information Systems

Accounting Information System (AIS) is a term which describes the financial recording system implemented by your organisation and consists of subsystems such as transaction processing system, general ledger/financial reporting system, fixed asset systems and management reporting system.

[1] How satisfied are you with your current accounting information system?

- ☐1 Very satisfied, no improvement required
- ☐2 Reasonably satisfied, although some improvement may be required
- ☐3 Needs improvements, but still usable
- ☐4 Dissatisfied, system requires major improvement

[2] Does your department use any software packages to assist in analysing an accounting data? ☐1 Yes ☐2No ☐ Don't Know

If yes, please specify_____________

[3] Please indicate your agreement with the importance of each of the following influences on the performance of the organisation.

In column 1, please rate the importance of each factor in ensuring the quality of an AIS from your perceptions and opinions.

In column 2, please rate the actual performance (achievement) on each of those factors by your organisation.

	Importance					Performance				
	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Poor	Fair	Good	Very good	Excellent
3.1. **Accurate**: the data which recorded is conforms to the actual value	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5
3.2. **Up-to-date** (timeliness): the data which is recorded in your system is timely	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5
3.3. **Complete**: all relevance value for a certain variable are recorded	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5
3.4 **Consistent**: the representation of the data value is the same in all cases	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5

[4] Please indicate how frequently you use the accounting data from AIS in each of the following areas

	Seldom	Occasionally	Fairly often	Often	Very often
4.1 Planning and budget	☐1	☐2	☐3	☐4	☐5
4.2 Decision making	☐1	☐2	☐3	☐4	☐5
4.3 Performance measurement	☐1	☐2	☐3	☐4	☐5
4.4 Cost control	☐1	☐2	☐3	☐4	☐5
4.5 Other (please specify)______________	☐1	☐2	☐3	☐4	☐5

[5] If you are going to evaluate the performance of your AIS, are the following factors important?

Please indicate the degree to which you agree with the following factors:

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
5.1 The systems are easy to use	☐1	☐2	☐3	☐4	☐5
5.2 The systems are able to automatically validate the data	☐1	☐2	☐3	☐4	☐5
5.3 The systems have an adequate and sufficient documentation for employees to follow	☐1	☐2	☐3	☐4	☐5
5.4 The systems are easy to modify and upgrade	☐1	☐2	☐3	☐4	☐5
5.5 The systems implement new data analysis tools (such as data mining)	☐1	☐2	☐3	☐4	☐5
5.6 The system have an effective data management approach such as, centralised database and data warehouse	☐1	☐2	☐3	☐4	☐5
5.7 Other (please specify)________________	☐1	☐2	☐3	☐4	☐5

2: Data Mining readiness

Data mining is the processes of analyzing the data in a value adding process to generate information and knowledge (pattern and relationships) to enhance the decision-making processes within the organisation. It uses an updated data analysis via a variety of techniques and tools to explore (summaries, comparison, analysis, forecast, estimate) the data.

	Yes	No	Not Sure
[6] Is the term data mining used in your organisation?	☐	☐	☐
[7] Is there any other term used that means data mining?	☐	☐	☐

If yes (please specify)________________

[8] Readiness toward technology – ***these questions seek to gain an understanding of your readiness to adopt technology in particular data mining.***

Please indicate the degree to which you agree with the following statements:

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
8.1. Technology gives me greater control over my daily work activities	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
8.2. Products and services that use the newest technologies are much more convenient to use	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
8.3. I prefer to use the most advanced technology available	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
8.4. Technology makes me more efficient in my occupation	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
8.5. I keep up with the latest technological developments in my areas of interest	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
8.6. I find myself having fewer problems than other people in making technology work for me	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
8.7. I am always open to learn about new and different technologies	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
8.8. It is easy to learn how to use technology	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
8.9. Overall, I find the technology useful for any task I need to accomplish	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
8.10. I think it would be very good to use data mining technology for analysing accounting data in addition to current methods.	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**

3: Data Mining Technologies Implementation

Adopters of Data Mining: Organisations that have implemented data mining tools or currently implementing any data mining software.

Data Mining tools: Software, which used to find patterns and regularities in sets of data (for example, Clementine, Enterprise Miner, Intelligent Miner, Darwin, Scenario, Knowledge SEEKER, Oracle9*i* Data Mining™, etc).

[9] Based on the definition, does your organisation utilise any data mining tools?

☐1 Yes, please specify______________
☐2 No, never used data mining tools (*please go to question 12)*
☐3 Don't know *(Please go to question 13)*

[10] For how many years has your organisation implemented data mining technologies?

☐1 Don't know
☐2 Less than 1 year
☐3 1 to less than 2 years
☐4 more than 2 years

[11] How important are the following factors in influencing your organisation's decision to employ data mining.

Please tick (√) your answer according to the scale given.

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
11.1 Adequate technical support from vendors	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
11.2 Compatibility of software with existing operating systems	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
11.3 Full support from top management	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
11.4 Effective and adequate training for staff	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
11.5 Technology savvy staff	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
11.6 Up-to-date ICT infrastructure	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
11.7 Changes in management trend within private sector	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
11.8 Directives from politicians.	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
11.9 An attempt to ensure public accountability	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
11.10 A sufficient financial resources	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**

Please skip question 12 and continue with question 13.

[12] If your organisation is NOT implementing any data mining tools, please answer the following questions.

Please indicate the degree to which you agree with the following reasons for **NOT** implementing data mining in your organisation:

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
12.1 Satisfied with current analysis method	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
12.2 Lack of expertise to implement data mining	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
12.3 Lack of awareness about data mining	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
12.4 Costly to implement new technology	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
12.5 Lack of top management support	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
12.6 Difficult to select appropriate software	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
12.7 Too complex and time-consuming	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
12.8 Lack of management policies	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
12.9 Having more pressing problems	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**

[13] The following questions explore your organisation's attitude toward adopting data mining. It does not matter if your organisation has implemented data mining or not. The questions are about your organisation's INTENTION to adopt data mining technology.

	No intent to adopt	Little intent to adopt	Moderate intent to adopt	Definite intend to adopt	Don't know
13.1 Does your organisation intend to adopt data mining?	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
	Less than 12 months	12 to 18 months	18 to 24 months	More than 24 months	No plans to adopt
13.2 If your organisation is intends to adopt data mining, how soon do you anticipate that it will operationally implement?	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**

4: Perception of Data Mining impact on organisational performance

This section seeks information about the impact that data mining technologies could bring to your organisation in terms of AIS performance and decision making process.

[14] Please indicate the degree to which you agree with the following statements about impacts you expect data mining bring to your organisation?:

	Strongly disagree	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
14.1 Lower down transaction cost	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
14.2 Increase the quality of information derived from AIS.	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
14.3 Increase overall AIS performance	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
14.4 Improve the quality of transaction	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
14.5 Reduce cycle time of my organisation	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
14.6 Fulfil information needs for the decision making	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
14.7 Provides decision support in supporting my decision making process	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**
14.8 Contributes to the speed of my decision making	☐**1**	☐**2**	☐**3**	☐**4**	☐**5**

5: Demographic Details

Direction: Please tick (√) your answer in the respective boxes.

[15] Sex

- ☐ Male
- ☐ Female

[16] Age

- ☐ less than 26 years
- ☐ 26-30 years
- ☐ 31-35 years
- ☐ 36-40 years
- ☐ 41-45 years
- ☐ 46-50 years
- ☐ above 50 years

[17] Highest qualification

- ☐ Doctoral
- ☐ Master's degree
- ☐ First degree/equivalent
- ☐ Diploma
- ☐ Secondary
- ☐ Others:____________

[18] In total, how many years experience do you have in government department?

- ☐ Less than 6 years
- ☐ 6-10 years
- ☐ 11-15 years
- ☐ 16-20 years
- ☐ More than 20 years

[19] How many years have you had experience with AIS?

- ☐ Less than 1 year
- ☐ 1-3 years
- ☐ 4 -6 years
- ☐ 7-9 years
- ☐ More than 10 years

[20] Number of years in the division/unit

- ☐ Less than 1 year
- ☐ 1-3 years
- ☐ 4 -6 years
- ☐ 7-9 years
- ☐ More than 10 years

[21] What is your primary job function?

- ☐ Accounting
- ☐ Finance
- ☐ Information Management
- ☐ Auditing
- ☐ Other:____________

[22] What is the level of your job responsibility?

- ☐ Non-management employee
- ☐ Middle Management
- ☐ Top Management

[23] How many employees are there in your whole organisation?

- ☐ >999
- ☐ 100-999
- ☐ 50 - 99
- ☐ 10 – 49
- ☐ <10
- ☐ Don't know

[24] Please rank your knowledge about data mining

- ☐ No knowledge
- ☐ Little knowledge
- ☐ Average knowledge
- ☐ Good knowledge
- ☐ Rich knowledge

If there is anything else that you would like to tell us about the implementation of data mining technologies in accounting information systems, please use the space provided below.

Your contribution to this research project is very greatly appreciated. Please return your questionnaire in the reply paid envelope provided. If the envelope has been mislaid, please forward to:

Mohd Shaari Abd Rahman
Jabatan Perakaunan dan Kewangan
Fakulti Pengurusan dan Ekonomi
Kolej Universiti Sains dan Teknologi Malaysia
21030 Kuala Terengganu, Terengganu

In order to follow up issues raised in this investigation and to improve the quality of my data. I'm hoping to interview some of the respondents to this questionnaire, probably in February 2006. If you are willing to be interviewed, would you please fill in the form below:

Your Name:____

Address: ____

____

Email: ____

Telephone:____

1: Sistem Maklumat Perakaunan

Sistem Maklumat Perakaunan (SMP) adalah terma berkaitan sistem perekodan kewangan yang digunapakai oleh organisasi. Ia meliputi sub-sistem pemprosesan transaksi, sistem lejer am/laporan kewangan, sistem asset tetap dan sistem laporan pengurusan.

[1] Apakah tahap kepuasan anda terhadap Sistem Maklumat Perakaunan yang digunapakai sekarang?

☐1 Sangat berpuashati, tiada penambahbaikan diperlukan
☐2 Berpuashati, bagaimanapun beberapa penambahbaikan diperlukan
☐3 Memerlukan penambahbaikan, tetapi masih boleh digunakan
☐4 Tidak berpuashati, sistem memerlukan penambaikan menyeluruh

[2] Adakah jabatan anda menggunakan mana-mana pakej perisian bagi membantu menganalisa data-data perakaunan?

☐1 Ya ☐2 Tiada ☐ Tidak Tahu
Jika Ya, sila jelaskan_____________

[3] Sila nyatakan tahap persetujuan anda terhadap faktor berikut mempengaruhi prestasi organisasi.

Ruang 1 , mengikut persepsi dan pendapat anda, nyatakan persetujuan anda kepada kepentingan faktor berikut dalam memastikan SMP berkualiti.
Ruang 2, Sila nyatakan tahap sebenar prestasi(pencapaian) setiap faktor yang dicapai oleh organisasi anda.

	Penting					Prestasi				
	Amat tidak setuju	Tidak setuju	Neutral	Setuju	Amat setuju	Lemah	Biasa	Bagus	Amat baik	Cemerlang
3.1. ***Accurate***: data yang direkod adalah sahih mengikut nilai sebenar	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5
3.2. ***Up-to-date*** (timeliness): data yang direkodkan dalam system adalah terkini	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5
3.3. ***Complete***: Semua nilai releven kepada sesuatu pemboleh ubah direkod	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5
3.4 ***Consistent***: gambaran nilai data adalah sama dalam semua kes.	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐3	☐4	☐5

[4] Sila nyatakan kekerapan anda menggunakan data perakaunan daripada SMP dalam bidang-bidang berikut:

	Jarang	Kadang-kadang	Sederhana Biasa	Selalu	Kerap Sekali
4.1 Perancangan dan Belanjawan	☐1	☐2	☐3	☐4	☐5
4.2 Pembuatan Keputusan	☐1	☐2	☐3	☐4	☐5
4.3 Penilaian Prestasi	☐1	☐2	☐3	☐4	☐5
4.4 Kawalan kos	☐1	☐2	☐3	☐4	☐5
4.5 Lain-lain (sila nyatakan)_____________	☐1	☐2	☐3	☐4	☐5

[5] Sekiranya anda bercadang untuk menilai prestasi SMP, adakah faktor berikut penting?

Sila nyatakan tahap persetujun anda kepada faktor berikut:

	Amat tidak setuju	Tidak setuju	Neutral	Setuju	Amat setuju
5.1 Sistem adalah mudah digunakan	☐1	☐2	☐3	☐4	☐5
5.2 Sistem mampu mengesahkan data secara otomatik	☐1	☐2	☐3	☐4	☐5
5.3 Sistem mempunyai dokumentasi yang lengkap dan mencukupi bagi diikuti oleh pekerja	☐1	☐2	☐3	☐4	☐5
5.4 Sistem mudah diubahsuai dan naik taraf	☐1	☐2	☐3	☐4	☐5
5.5 Sistem melaksanakan alatan analisis data yang baru (sepeti alatan data mining)	☐1	☐2	☐3	☐4	☐5
5.6 Sistem mempunyai pengurusan data yang efektif seperti pengkalan data berpusat dan gedung data (*data warehouse*)	☐1	☐2	☐3	☐4	☐5
5.7 Lain-lain (Sila nyatakan)_______________	☐1	☐2	☐3	☐4	☐5

2: Kesediaan terhadap Data Mining

Data mining – adalah proses-proses penganalisaan data dalam proses menambahnilai untuk menjana maklumat dan pengetahuan (berupa corak dan hubungkait antara data) bagi memperkasa proses pembuatan keputusan dalam organisasi. Ia menggunakan data analisis terkini melalui pelbagai teknik dan alat penerokaan data (ringkasan, perbandingan, analisa, ramalan, anggaran).

	Ya	Tidak	Tak Pasti
[6] Adakah terma 'data mining' diguna dalam organisasi?	☐	☐	☐

[7] Adakah terdapat istilah lain digunapakai membawa maksud data mining?

☐**Ya** ☐**Tidak** ☐**Tidak Pasti**

Jika Ya (sila nyatakan)_________________

[8] Kesediaan terhadap teknologi-*soalan berikut bertujuan mendapatkan pemahaman terhadap kesediaan anda untuk menggunapakai teknologi terutamanya data mining.*

Sila nyatakan tahap persetujuan anda kepada kenyataan dibawah:

	Amat tidak setuju	**Tidak setuju**	**Neutral**	**Setuju**	**Amat setuju**
8.1. Teknologi memberikan saya lebih kawalan terhadap aktiviti kerja harian..	☐1	☐2	☐3	☐4	☐5
8.2. Produk dan servis yang menggunakan teknologi terbaru adalah lebih mudah/selesa digunakan	☐1	☐2	☐3	☐4	☐5
8.3. Saya mengutamakan penggunaan teknologi terkini	☐1	☐2	☐3	☐4	☐5
8.4. Teknologi membuatkan saya lebih efisyen dalam pekerjaan	☐1	☐2	☐3	☐4	☐5
8.5. Saya sentiasa mengikuti perkembangan teknologi terkini yang berkait bidang kegemaran saya	☐1	☐2	☐3	☐4	☐5
8.6. Saya kurang bermasalah berbanding orang lain dalam membuatkan teknologi berguna kepada saya	☐1	☐2	☐3	☐4	☐5
8.7. Saya sentiasa terbuka untuk mempelajari teknologi terbaru dan berlainan.	☐1	☐2	☐3	☐4	☐5
8.8. Adalah mudah belajar menggunakan teknologi	☐1	☐2	☐3	☐4	☐5
8.9. Keseluruhannya, teknologi berguna untuk apa juga tugas yang perlu diselesaikan	☐1	☐2	☐3	☐4	☐5
8.10. Saya fikir, adalah baik untuk menggunakan teknologi data mining bagi menganalisa data perakaunan sebagai tambahan kepada kaedah sedia ada	☐1	☐2	☐3	☐4	☐5

3: Implementasi Teknologi Data Mining

Penerima pakai Data Mining: Organisasi yang telah dan sedang melaksanakan mana-mana perisian data mining.

Alatan data mining: Perisian yang diguna bagi tujuan pencarian corak dan hubungan dalam set data.(contoh perisian, Clementine, Enterprise Miner, Intelligent Miner, Darwin, Scenario, Knowledge SEEKER, Oracle9*i* Data Mining^{TM}, etc).

[9] Berasaskan definisi, adakah organisasi anda menggunakan alatan data mining?

☐1 Ya, sila nyatakan_______________

☐2 Tidak pernah menggunakan alatan data mining (*Sila ke soalan12)*

☐3 Tidak tahu *(Sila ke soalan 13)*

[10] Sudah berapa tahun kah organisasi anda melaksanakan teknologi data mining ini?

☐1 Tidak Tahu

☐2 Kurang 1 tahun

☐3 1 hingga 2 tahun

☐4 lebih 2 tahun

[11] Bagaimana pentingnya faktor berikut dalam mempengaruhi keputusan organisasi untuk melaksanakan data mining.

Tandakan (√) pada jawapan anda mengikut tahap persetujuan.

	Amat tidak setuju	**Tidak Setuju**	**Neutral**	**Setuju**	**Amat setuju**
11.1 Sokongan teknikal mencukupi dari vendor	☐1	☐2	☐3	☐4	☐5
11.2 Keserasian perisian dengan system operasi sedia ada.	☐1	☐2	☐3	☐4	☐5
11.3 Sokongan penuh pihak pengurusan atasan	☐1	☐2	☐3	☐4	☐5
11.4 Latihan staf yang efektif dan memadai	☐1	☐2	☐3	☐4	☐5
11.5 Staf yang teknologi 'savvy'	☐1	☐2	☐3	☐4	☐5
11.6 Infrastruktur ICT yang terkini	☐1	☐2	☐3	☐4	☐5
11.7 Perubahan dalam corak pengurusan dikalangan sektor swasta.	☐1	☐2	☐3	☐4	☐5
11.8 Arahan dari ahli politik.	☐1	☐2	☐3	☐4	☐5
11.9 Usaha memastikan akauntibiliti awam	☐1	☐2	☐3	☐4	☐5
11.10 Peruntukan kewangan yang mencukupi	☐1	☐2	☐3	☐4	☐5

Elak dari menjawap soalan 12 dan sila terus ke soalan13.

[12] Sekiranya organisasi TIDAK melaksanakan mana-mana alat data mining, sila jawab soalan berikut.
Sila nyatakan tahap setuju anda dengan kenyataan dibawah berkaitan alasan untuk **TIDAK** melaksanakan data mining dalam organisasi anda:

	Amat tidak setuju	Tidak Setuju	Neutral	Setuju	Amat bersetuju
12.1 Puas hati dengan kaedah analisis data sedia ada	☐1	☐2	☐3	☐4	☐5
12.2 Kekurangan kepakaran untuk melaksanakannya	☐1	☐2	☐3	☐4	☐5
12.3 Kurang kesedaran terhadap data mining	☐1	☐2	☐3	☐4	☐5
12.4 Kos begitu tinggi bagi laksanakan teknologi baru	☐1	☐2	☐3	☐4	☐5
12.5 Kurang sokongan pihak pengurusan atasan	☐1	☐2	☐3	☐4	☐5
12.6 Sukar memilih perisian yang sesuai	☐1	☐2	☐3	☐4	☐5
12.7 Terlalu sukar dan memakan masa	☐1	☐2	☐3	☐4	☐5
12.8 Kekurangan polisi pengurusan	☐1	☐2	☐3	☐4	☐5
12.9 Mempunyai masalah lain yang lebih penting	☐1	☐2	☐3	☐4	☐5

[13] Soalan berikut meneroka sikap organisasi anda terhadap penggunaan data mining. Tidak mengambil kira sama ada organisasi anda melaksanakan data mining atau tidak. Soalan adalah berkaitan NIAT/CADANGAN organisasi kepada penggunaan teknologi data mining.

13.1 Adakan organisasi anda bercadang/berniat untuk menggunakan data mining?	Tiada Niat	Sedikit Niat	Niat Sederhana	Memang berniat	Tidak tahu
	☐1	☐2	☐3	☐4	☐5
13.2 Sekiranya organisasi bercadang menggunakan data mining, bilakah akan dilaksanakan operasinya?	Kurang dari 12 bulan	12 hingga 18 bulan	18 hingga 24 bulan	Lebih dari 24 bulan	Tiada perancangan untuk guna data mining
	☐1	☐2	☐3	☐4	☐5

4: Persepsi impak Data Mining terhadap prestasi organisasi

Seksyen ini bertujuan mandapatkan maklumat berkaitan impak yang boleh dibawa oleh teknologi data mining kepada organisasi anda terutamanya dari segi prestasi Sistem Maklumat Perakaunan dan process pembuatan keputusan.

[14] Sila nyatakan sama ada setuju atau tidak dengan kenyataan berkaitan impak yang diramalkan boleh dibawa oleh data mining kepada organisasi anda?

	Amat tidak setuju	Tidak setuju	Neutral	Setuju	Amat bersetuju
14.1 Mengurangkan kos transaksi	☐1	☐2	☐3	☐4	☐5
14.2 Meningkatkan kualiti maklumat yang diperolehi dari Sistem Maklumat Perakaunan.	☐1	☐2	☐3	☐4	☐5
14.3 Meningkatkan prestasi Sistem Maklumat Perakaunan secara keseluruhannya	☐1	☐2	☐3	☐4	☐5
14.4 Meningkatkan kualiti transaksi	☐1	☐2	☐3	☐4	☐5
14.5 Mengurangkan kadar masa/pusingan masa bagi organisasi	☐1	☐2	☐3	☐4	☐5
14.6 Memenuhi keperluan maklumat kepada pembuatan keputusan	☐1	☐2	☐3	☐4	☐5
14.7 Menyediakan sokongan dalam menyokong keputusan dalam prosess pembuatan keputusan.	☐1	☐2	☐3	☐4	☐5
14.8 Menyumbang kepada penyegeraan membuat keputusan	☐1	☐2	☐3	☐4	☐5

5: Demografik

Arahan: Tandakan (√) jawapan anda pada kotak berkaitan.

[15] Jantina

- ☐ Lelaki
- ☐ Perempuaan

[16] Umur

- ☐ kurang dari 26 tahun
- ☐ 26-30 tahun
- ☐ 31-35 tahun
- ☐ 36-40 tahun
- ☐ 41-45 tahun
- ☐ 46-50 tahun
- ☐ lebih 50 tahun

[17] Pendidikan tertinggi

- ☐ Doktor Falsafah
- ☐ Sarjana
- ☐ Sarjana Muda/setaraf
- ☐ Diploma
- ☐ Menengah/Sijil
- ☐ Lain-lain:____________

[18] Berapa tahun pengalaman keseluruhannya dalam perkhidmatan kerajaan?

- ☐ kurang dari 6 tahun
- ☐ 6-10 tahun
- ☐ 11-15 tahun
- ☐ 16-20 tahun
- ☐ lebih 20 tahun

[19] Berapa tahun pengalaman berkaitan Sistem Maklumat Perakaunan?

- ☐ kurang dari 1 tahun
- ☐ 1-3 tahun
- ☐ 4 -6 tahun
- ☐ 7-9 tahun
- ☐ lebih 10 tahun

[20] Berapa tahun bersama bahagian/unit ini.

- ☐ kurang 1 tahun
- ☐ 1-3 tahun
- ☐ 4 -6 tahun
- ☐ 7-9 tahun
- ☐ lebih 10 tahun

[21] Apakah tugas dan peranan utama anda?

- ☐ Perakaunan
- ☐ Kewangan
- ☐ Pengurusan Maklumat
- ☐ Pengauditan
- ☐ Lain:____________

[22] Tahap tanggungjawap jawatan anda?

- ☐ Kumpulan Sokongan
- ☐ Pengurusan Pertengahan
- ☐ Pengurusan Atasan

[23] Berapa jumlah keseluruhan pekerja dalam organisasi?

- ☐ >999
- ☐ 100-999
- ☐ 50 - 99
- ☐ 10 – 49
- ☐ <10
- ☐ Tidak tahu

[24] Apakah tahap pegetahuan anda terhadap data mining

- ☐ Tiada pengetahuan
- ☐ Sedikit pengetahuan
- ☐ Sederhana
- ☐ Berpengetahuan
- ☐ Banyak pengetahuan

Sekiranya terdapat lain-lain hal yang ingin diajukan kepada kami berkaitan implementasi teknologi 'data mining' dalam Sistem Maklumat Perakauan, sila gunakan ruang di bawah.

Sumbangan saudara/saudari kepada penyelidikan ini amat di hargai. Sila kembalikan soalselidik ini menggunakan sampul surat beralamat sendiri yang disediakan. Sekiranya berlaku kehilangan, pohon kemukakan soalselidik ke alamat

Mohd Shaari Abd Rahman
Jabatan Perakaunan dan Kewangan
Fakulti Pengurusan dan Ekonomi
Kolej Universiti Sains dan Teknologi Malaysia
21030 Kuala Terengganu, Terengganu

Susulan kepada isu-isu yang dibangkitkan dalam soalselidik ini dan bagi meningkatkan kualiti data, saya berharap dapat menemuramah beberapa responden, sekitar Februari 2006. Sekiranya saudara/saudari sudi ditemuramah, sila lengkapkan maklumat dibawah:

Name: ____

Alamat:____

____

Email: ____

Telephone: ____

Appendix Two: Interview covering Letter and interview protocol

Appendix 2.1 (Interview cover letter)

UNIVERSITY OF TASMANIA
School of Accounting and Corporate Governance

«FirstName» «LastName»
«JobTitle»
«Company»
«Address1»
«Address2» «City»
«State» «PostalCode»

<Date>

Dear «FirstName»

You may recall that you recently completed a mail survey relating to my Doctoral degree in Accounting at the University of Tasmania. Many thanks for this. As you may remember, I am conducting research into the utilisation of Data Mining Technologies within the Accounting Information System in the Public Sector – A Country Study – Malaysia.

In your response to the mail survey you indicated a willingness to participate in the interview stage of the study. This interview is crucial part of my study, which will improve the richness of the quality of the results within this study. Your views and opinion would be very important to this research. We would now like to ask whether you are still willing to participate. Please find the abbreviated interview schedule attached. It is proposed to hold interviews during March 2006, could you please indicate your availability on <date> 2006 at <time> or could you indicate a suitable date and time. It is envisaged that the interview would be conducted on your premises, and take approximately 60 to 90 minutes. It is anticipated that the interview will be audio recorded, and that you will be given the opportunity to review and amend any material including any transcripts from these recordings.

Participation in this process is entirely voluntary and evidenced by signing the attached consent form. Please be assured, in any case, that you can decline to answer any question, and can withdraw without effect or explanation. If you withdraw, you may elect to withdraw any data you have supplied to date.

Although I will know the identity of interviewees and their organisations, this will not be disclosed in the thesis or any other research output. However, direct quotations from the interview transcripts may be cited, which will be presented in quotation marks identified by the case name and the participant's position title. It follows that it is possible that your responses may be identifiable to you or your organisation. If you are concerned that any of your responses may be identifiable to you or your organisation, and wish to avoid this as a possibility, please carefully peruse your interview transcript, and modify what you deem fit for this purpose.

All raw data collected from this study will be securely stored at the School of Accounting and Finance for a period of five years. At the expiry of this five year period, the data will be destroyed. I would be happy to give you a summary of my findings; simply let me know at the interview or send me an email afterwards.

This study has been approved by the Human Research Ethics Committee (Tasmania) Network. If you have any concerns of an ethical nature or complaints about the nature in which the project is conducted, you may contact the Executive Officer of the Human Research Ethics Committee (Tasmania) Network.

Executive Officer: Amanda McAully
Email: Amanda.McAully@utas.edu.au
Phone: 61 3 62262763
Fax: 61 3 62267148

If you wish to participate in this process, please sign the below and forward to me by fax or mail. I can be contacted on +61 (03) 62262801 (Phone), +61 (03)62267845 (Fax) or msabd@utas.edu.au (email) if you have any further queries.

I look forward to hearing from you.

Yours sincerely

Mohd Shaari Abd Rahman
PhD Candidate
Student ID 039115
School of Accounting and Finance
University of Tasmania

Co-signed:

Dr Trevor Wilmshurst
Senior Lecturer
School of Accounting and Finance
University of Tasmania

Appendix 2.2

Interview protocol (guide)

The Utilisation of Data mining technologies within Accounting Information Systems in Public Sector- A country study: Malaysia

Organisation name:
Interviewee's name:
Business profile:
Location:
Date:
Start time of the interview:
Finish time of the interview:

Section 1: General Information (Demographic)

Please tell me about yourself.
1. Your background.
    1) Education, and working experience
    2) Your experience with accounting information systems
    3) Your role in the organisation, time in that role

2. Your organisation.
    1) Your department
        - Finance, Accounting
        - Information systems /IT
        - Senior Executive
        - Other
    2) Your main role relative to accounting information. Do you primarily:
        - Collect accounting information
        - Manage those who collect accounting information
        - Use accounting information in tasks
        - Manage those who use accounting information in tasks
        - Work as an information systems professionals
        - Manage those who work as information systems professionals
        - Use information generated in decision making

Section 2: Accounting Information Systems (AIS)

Please tell me something about your organisation's accounting information systems (AIS)?
1. How large is the AIS? (Number of different systems /packages, Number of staff)
2. What kind of systems are you using for AIS? Please name.
3. How old is the AIS? (The age, maturity of the system)
4. What is the organisational structure of the AIS and how does your role fit in the structure?
5. Overall, what is your opinion on the performance of the AIS? Why do you believe this?
6. What are the criteria that you consider in evaluating the performance of the AIS?
7. What are the main objectives you believe are implicit in the use of an AIS by your organisation?

Section 3. Data mining readiness

1. Do you know anything about data analysis software? What do you think about the options available? What is your organisation presently using? Is your organisation using the 'best software' for purpose? What do think on the emergence of many data analysis software in the market?
2. Can you describe to me, what type of person you are when dealing with computer technology? Do you see technology as an enabler to increase efficiency in your work? Or perhaps you see it as panacea? Do you like to try new and latest technology?
3. If you are offered the opportunity to a workshop or seminar which deals with new and latest technology, are you willing to go?
4. I am sure you are using computer in your work, do you feel confident with everything that you do with that computer. If you use a computer, What roles do you use the computer for?
5. Overall, how do you perceive on the rapid development in the technology? And its implication for your area of work.
6. Have you ever heard about data mining technology? What is you opinion on that technology?

Note for interviewer: The interviewer will briefly explain the meaning of data mining and examples of software available in the market.

Data mining is the processes of analyzing the data in a value adding process to generate information and knowledge (pattern and relationships) to enhance the decision-making processes within the organisation. It uses an updated data analysis via a variety of techniques and tools to explore (summaries, comparison, analysis, forecast, estimate) the data.
Data Mining tools: Software, which used to find patterns and regularities in sets of data (for example, Clementine, Enterprise Miner, Intelligent Miner, Darwin, Scenario, Knowledge SEEKER, DataMind Data Cruncher).

Section 4: Data Mining implementation

1. Do you have data mining software installed in your AIS at the moment?

Note for interviewer: If they don't have Data Mining installed, proceed with these questions: if YES, go to questions 10 onwards.

2. What do you believe are the major reasons for your organisation not having any data mining software?
3. Has your department investigated this type of software but concluded that it seems not suitable?
4. Perhaps your organisation have different name of similar activities done under data mining, do you have one? What is it?
5. Would you mind to share with me how your accounting data is analysed before it is presented to decision makers?
6. What type of analysis that normally you have done to those data?
7. Do you using any software in helping you to analyse that data? What is it?
8. Do you have data analysis policies and model on how the data should be analyse? Can I have a copy after this interview?
9. Do you think your department will consider data mining software afterwards?

Go to conclusion

10. What are the main reason(s) why your department implementing such a technology?
11. Do you think the technology help to increase capacity and ability of your decision making process? What about AIS performance, do you think that this technology has improved your AIS ability.
12. Do you agree if I say, your departments' ability to implement the technology has improved your AIS functions?
13. We have defined some factors which might be influence department to implement data mining technology. Which of these factors do you think are critical and important in the decision to employ new technology such as data mining. Would you be able to give a mark for each of these factors on the ten point scale, 10 as very important, 1 as not important at all.
    a. Adequate technical support from vendor
    b. Use friendly interfaces
    c. Availability of good quality data
    d. Problem solving ability
    e. Top management commitment
    f. Optimistic department
    g. Nature of the software (easy to use)
    h. Clear department policy about data analysis
    i. The structure of organisation
    j. The culture in your organisation
    k. Financial resource
    l. Skill staff
    m. Political influences
    n. Government intervention
    o. Data analysis trend which came from private sector

Do your think these factors are appropriate? Why, why not?
Are there other factors that you think may be important but were not included in this list?

Conclusion:

Is there anything I have not asked that you feel is important when discussing about data mining software, tools, technologies in accounting information systems?

Is there any one else that you would recommend talking to in relation to this topic?

Would you like some of the feedback from this research regarding to the findings of the research?

If you would like, we will supply a copy of what we believe you told us, and how we have interpreted what you said, so that you can correct the impressions that we have taken from your responses.

Thank you very much for your precious time and your valuable help!

Appendix Three: Interview Schedule (Brief Version)

Interview Schedule (Brief Version)
The Utilisation of Data mining technologies within
Accounting Information Systems in Public Sector-
A country study: Malaysia

Organisation name:______________________________
Interviewee's name: _____________________________
Location:______________________________________ Date:______________________
Start time of the interview:________________________ Finish time: _______________

Section 1: General Information (Demographic)

Please tell me about yourself.
1. Your background (education, working experiences, roles in organisation)
2. Your organisation (department and main role relates to accounting information)

Section 2: Accounting Information Systems (AIS)

Questions relates to AIS in your organisation (size, types of system, maturity, structure, performance, criteria in performance evaluations, objectives of the systems implementation)

Section 3. Data mining readiness

The questions relates to your awareness of the existence of data mining techniques and some questions on how you perceived ICT in your everyday activities.

Section 4: Data mining implementation
Primary question of this section is whether data mining were installed or adopted in your organisation. It then will follows with related questions to the adopters and non-adopters.

Questions for non-adopters will mainly asked about the reasons not having such technology, what other types of analysis being taken to the accounting data, data analysis procedure and your intention to consider data mining software in the future. While for adopters, the questions will mainly asked the reasons and factors that drove to the implementation, impact on AIS performance and decision making process.

Conclusion:
For this part, the questions mainly asked about your recommendation and feedback about this topic.

Thank you very much for your precious time and your valuable help!

Appendix Four: Consent form

CONSENT FORM

Title of Project: **The Utilisation of Data Mining Technologies within the Accounting Information System in the Public Sector- A Country Study: Malaysia**

---

1. I have read and understood the 'Information Sheet' for this study.
2. I understand that the study involves the interviews which likely to take approximately 1 to 1.5 hour and proposed to be held in March 2006.
3. I understand that all research data will be securely stored on the University of Tasmania premises for at least five years, and will be destroyed when no longer required.
4. Any questions that I have asked have been answered to my satisfaction.

6. I understand that I may be identifiable due to my official position or title, or the nature of my work / occupation, but I agree that research data gathered from me for the study may be published provided that my identity is not disclosed.
7. I understand that my identity will be kept confidential and that any information I supply to the researcher(s) will be used only for the purposes of the research.
8. I agree to participate in this investigation and understand that I may withdraw at any time without any effect, and if I so wish, may request that any data I have supplied to date be withdrawn from the research.

Name of Participant:

Suggested Date for interview: Time:

Signature: Date:

Statement by Investigator

☐ I have explained this project and the implications of participation in it to this volunteer and I believe that the consent is informed and that he/she understands the implications of participation

If the Investigator has not had an opportunity to talk to participants prior to them participating, the following must be ticked.

☐ The participant has received the Information Sheet in which my details have been provided so that participants have had opportunity to contact me prior to them consenting to participate in this project.

Name of investigator: ____

Signature of investigator: _______________________________ Date:_________________

Appendix Five: Statistical Analysis Decision Tree

Statistical Analysis Decision Tree

Determine which variable is independent (IV) and which is dependent (DV) in your hypothesis or research question

Determine each variable's level of measurement (nominal, ordinal, interval/ratio) Dichotomies can be treated as any level and many ordinal measures with equal-appearing intervals can be used as interval/ratio measures.

Run frequencies and appropriate descriptive statistic (mode, med, mean) to assess whether each variable is really a variable (not a constant) in your sample

Decide on the appropriate statistics to use to analyse relationships between the independent and dependent variables.

Compare Means of DV (interval/ratio) between two categories of an independent variable: use **T-test** Among three or more categories of IV : use **ANOVA**

1. Test relationship between nominal and/or ordinal variables: use **Chi-square**
2. If at least one variable is nominal: use **Lambda**
3. If both are ordinal: use **Gamma**
4. If the variables are ordinal ranks: use **Spearman rho**

Test a relationship between two interval/ratio variables: use **Pearson r** correlation If there are two or more IV use **Multiple Correlation ®** and **Linear Regression**

If the probability of obtaining that statistic by chance is less than 0.05 (p<.05) then reject the null hypothesis of no difference or no relationship, and declare there is a significant relationship between the two variables.

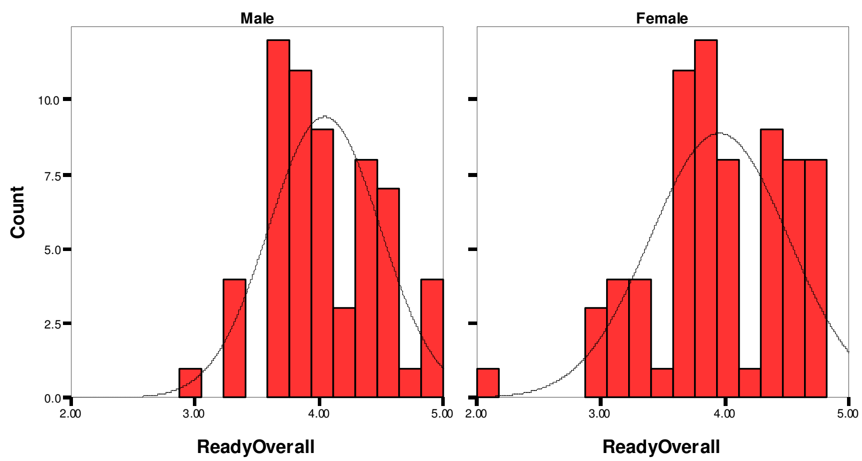
For Lambda, Gamma, Spearman, and Pearson r correlations assess the strength of the relationship: around 0 to.25 is low, .25 to .60 is moderate, and .60 to 1.0 is strong.
The direction (+ or -) also tells your if it's a positive relationship (both increase or decrease in same direction) or an inverse on (as one variable increase, the other decreases).

Statistical Analysis Decision Tree (Adapted from Nardi, 2006)

Appendix Six: Testing of Assumption (T-Test, ANOVA) and Normal Plot

Appendix 6.1: Testing assumption of t-test

As for the assumption of normality, the t-test is reliable as long as the samples suggest symmentric, bell-shaped data without gross departures from a normal distribution (Carver & Nash, 2005).



Though not perfectly normal, these are reasonably symmetrical and bell-shaped, and suitable for performing the t-test.

Appendix 6.2: Assumption of ANOVA

Before performing the analysis, assumptions required for ANOVA has to be reviewed first. An independent measures ANOVA requires three conditions for reliable results (Carver & Nash, 2005).

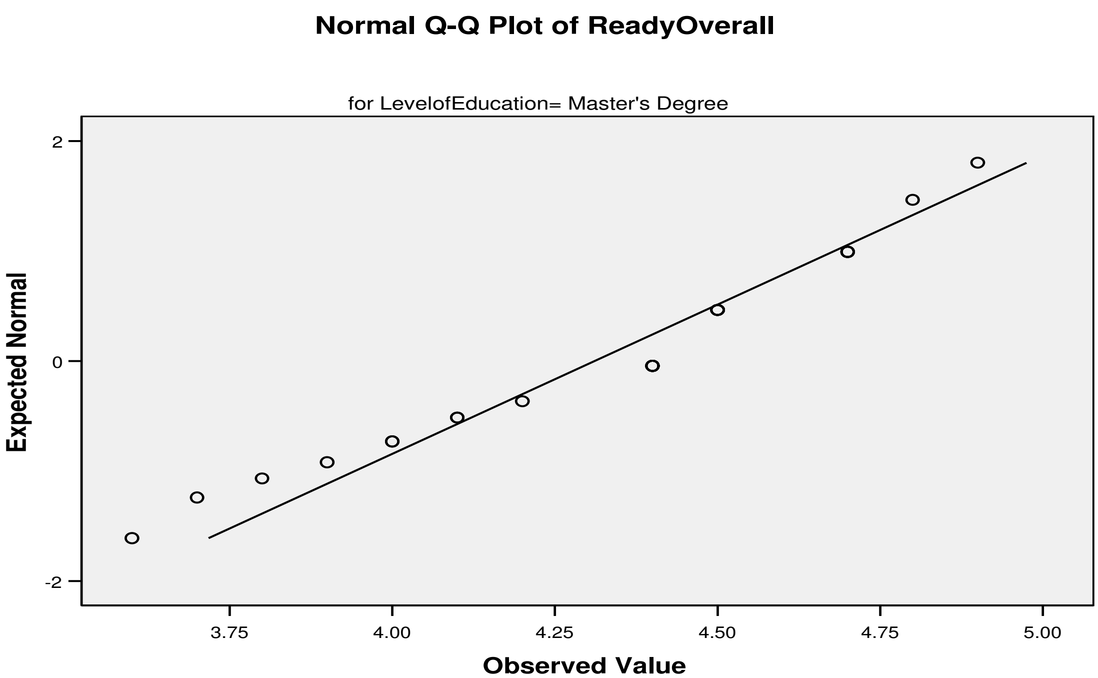
1. Independent samples
2. Normal populations
3. Homogeneity (or equality) of population variances

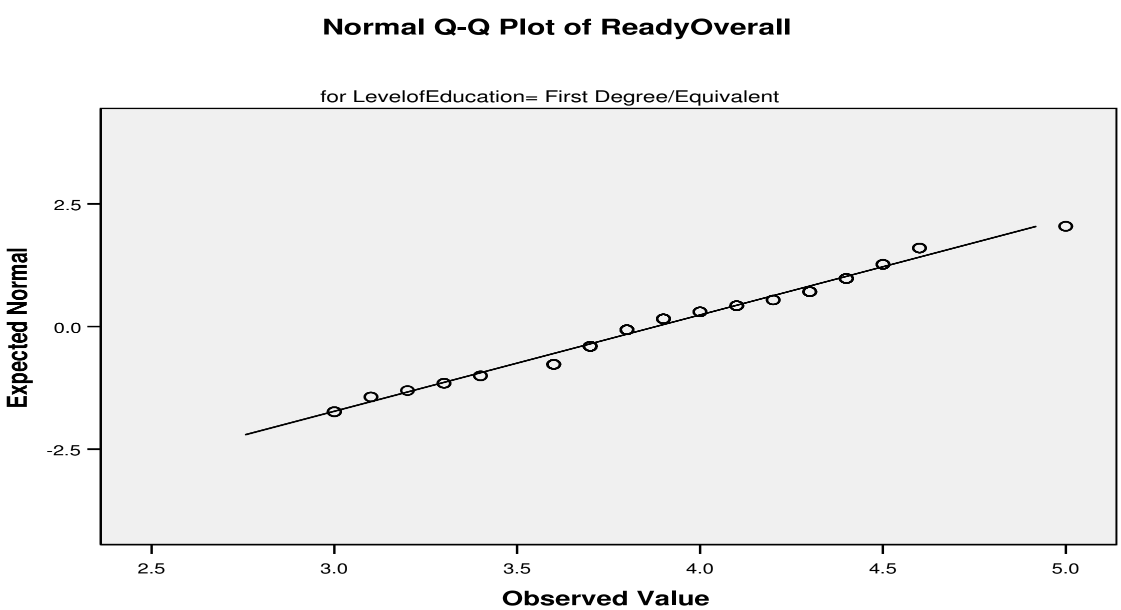
Levene's Test is used to check for equality of variance while a normal probability plot is used to check for normality (Francis, 2004). The results of Levene's Test below shows that all levene's test was not significant which indicate that all groups have similar variance. Therefore, assumption of homogeneity is not violated. Here also presents a normal probability plot for checking its normality.

Table A6.2aTest of Homogeneity of Variances: Education

Levene Statistic	df1	df2	Sig.
.818	2	129	.444

Figure A6.2a Result of test for normality





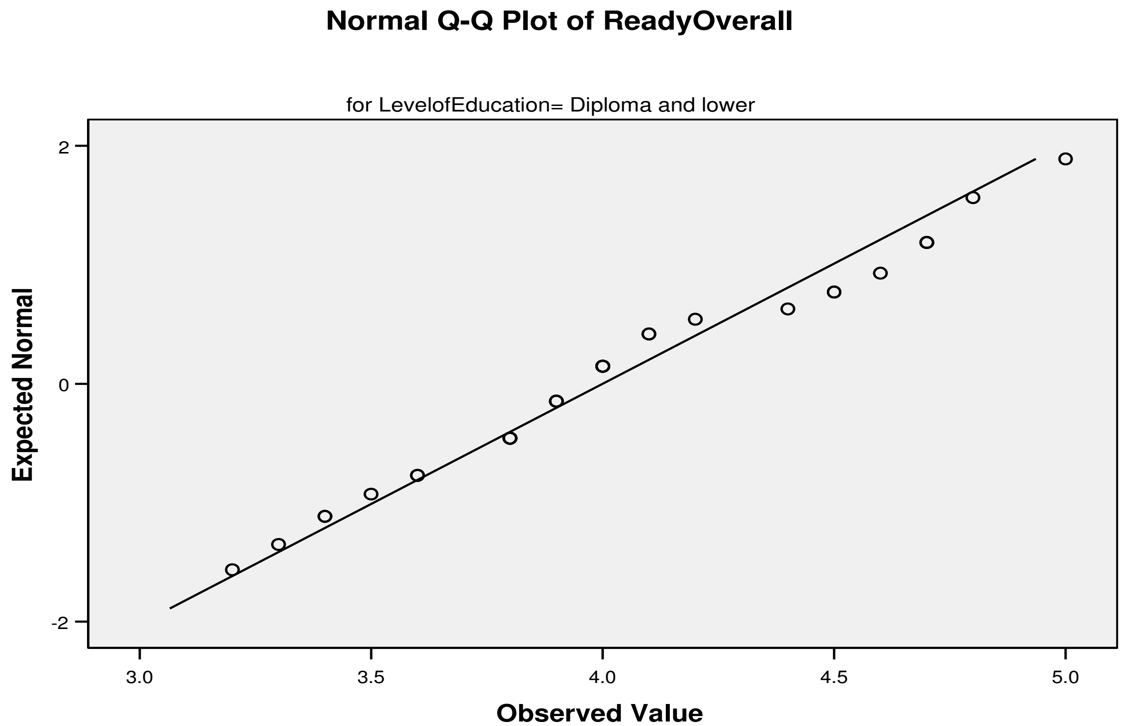
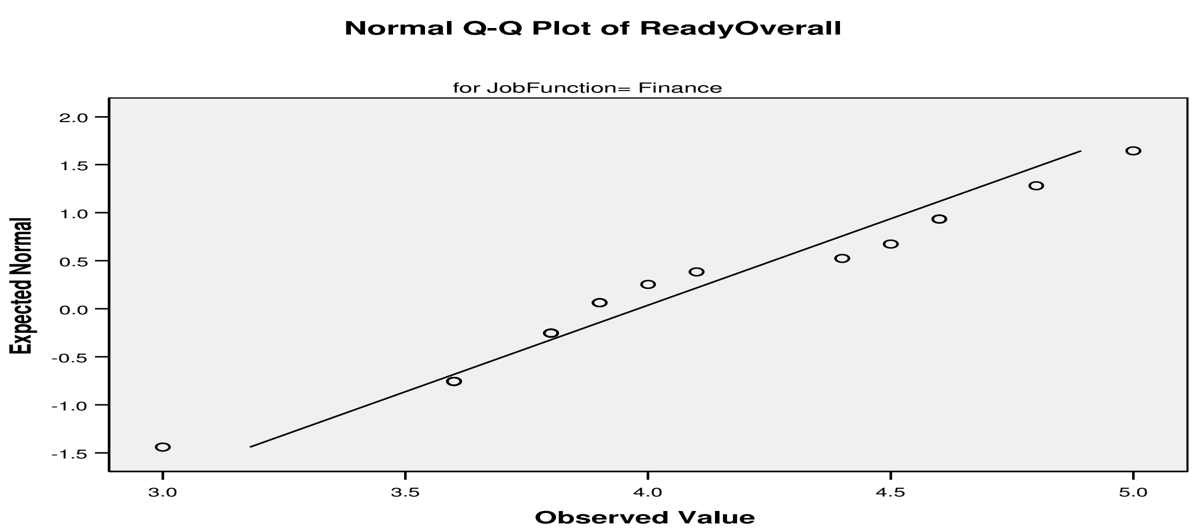


Table A6.2b: Test of Homogeneity of Variances: Job Function

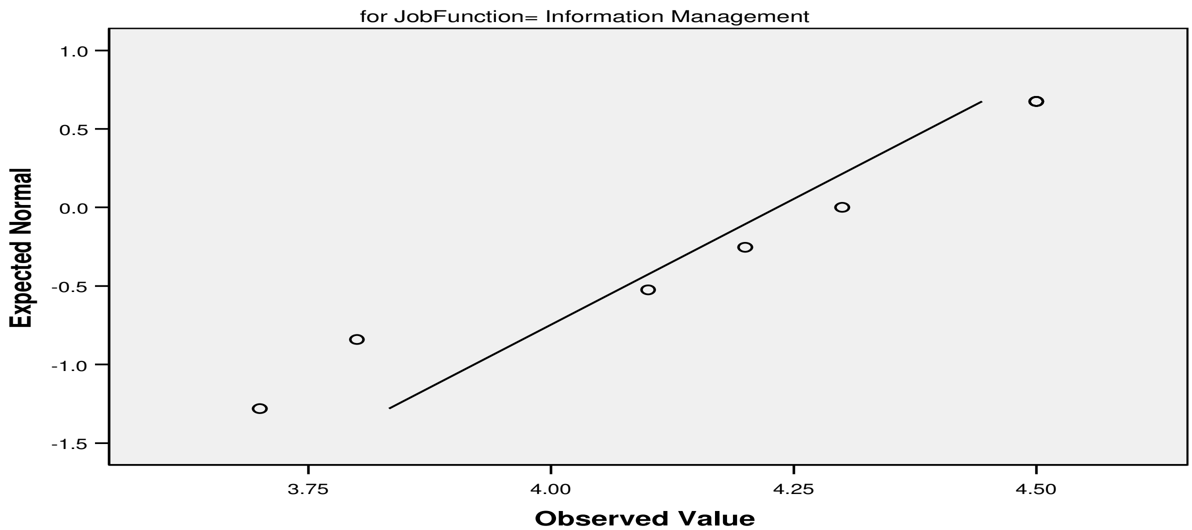
ReadyOverall

Levene Statistic	df1	df2	Sig.
1.188	3	112	.318

Figure A6.2b Result of test for normality



Normal Q-Q Plot of ReadyOverall



Normal Q-Q Plot of ReadyOverall

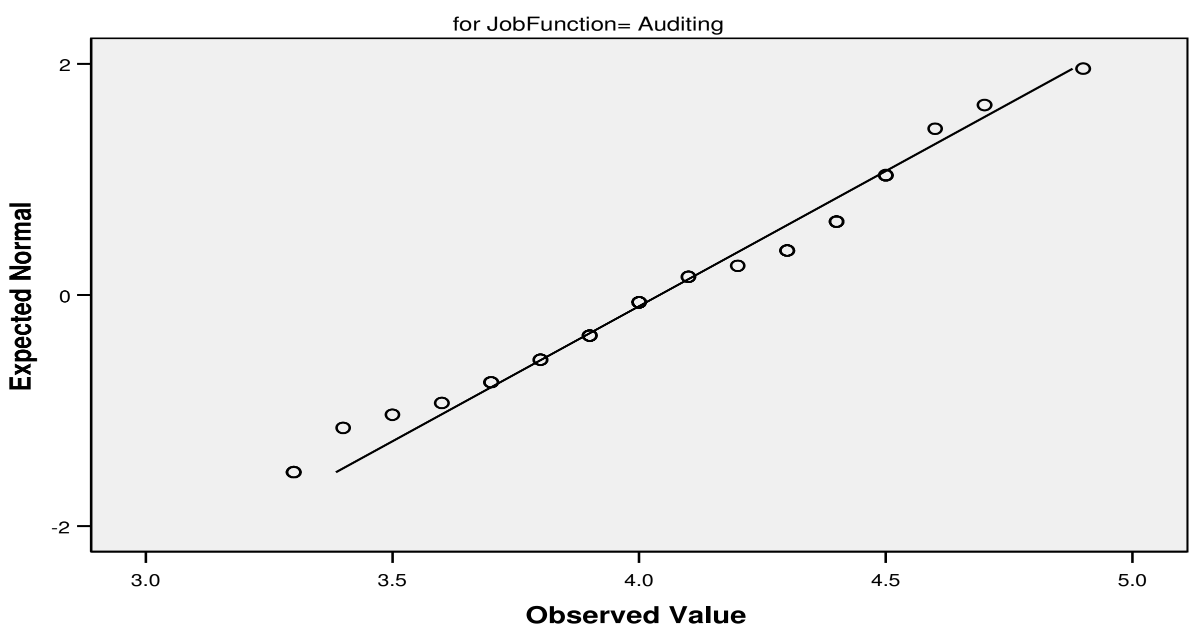


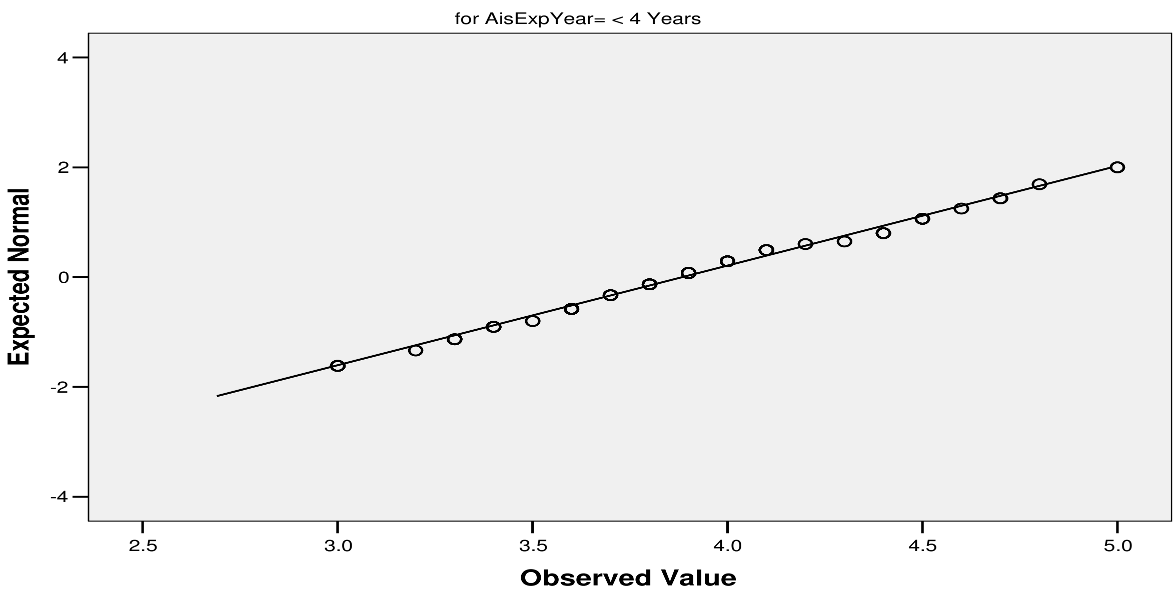
Table A6.2c:Test of Homogeneity of Variances: Experience in AIS

ReadyOverall

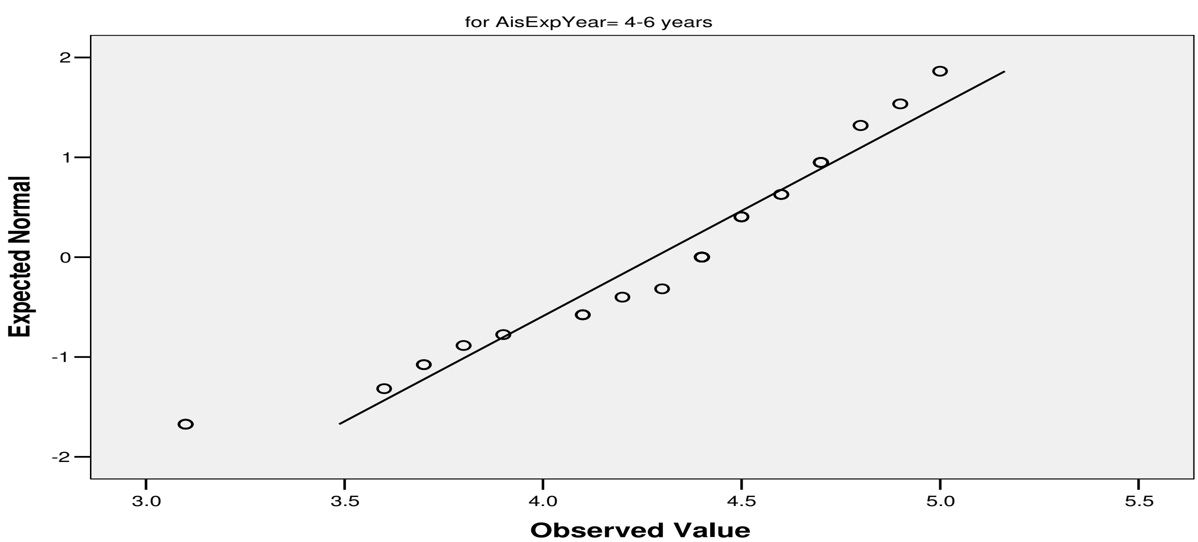
Levene Statistic	df1	df2	Sig.
2.647	2	127	.075

Figure A6.2c Result of test for normality

Normal Q-Q Plot of Readiness overall



Normal Q-Q Plot of Readiness overall



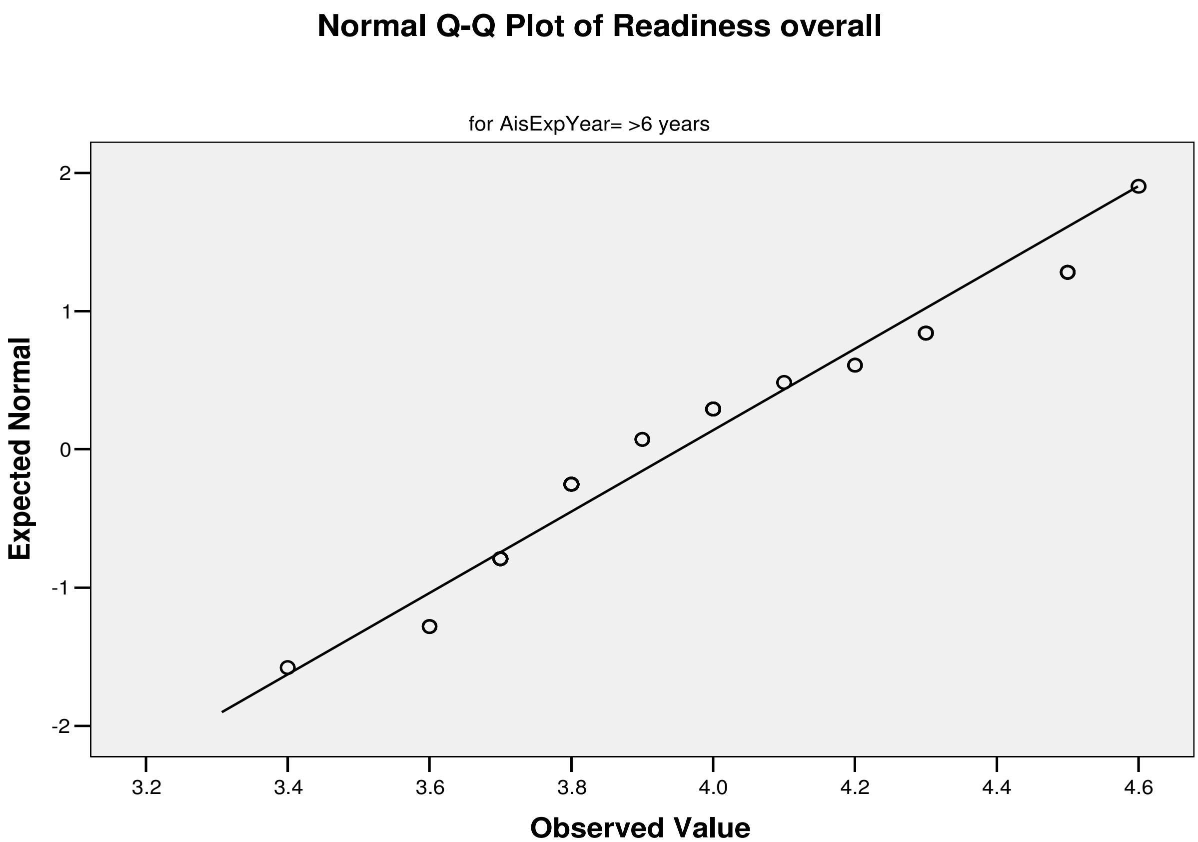
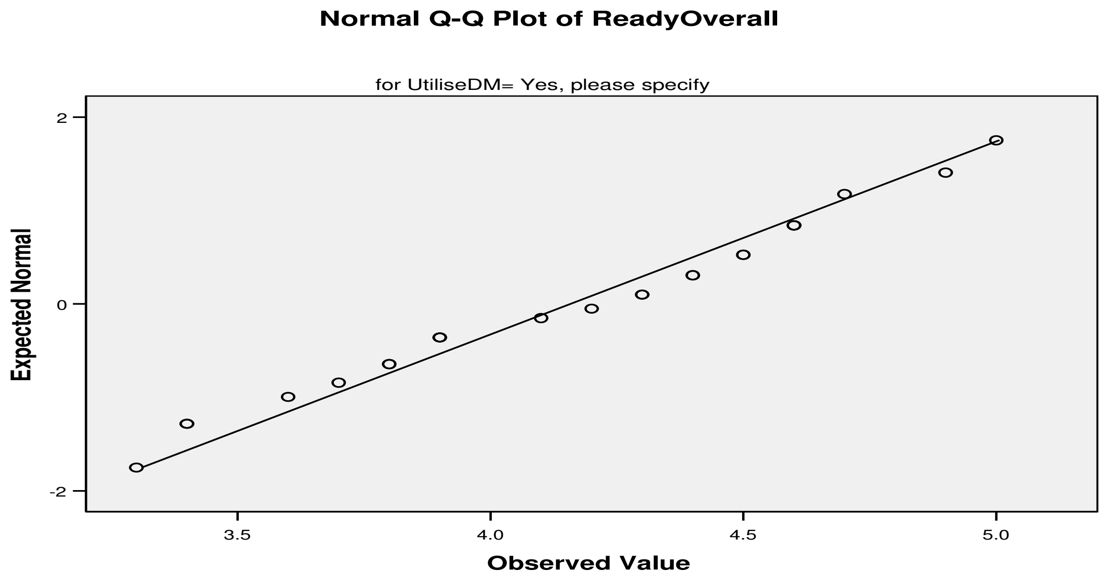

Normal Q-Q Plot of Readiness overall
for AisExpYear= >6 years
Expected Normal
Observed Value
2
1
0
-1
-2
3.2
3.4
3.6
3.8
4.0
4.2
4.4
4.6

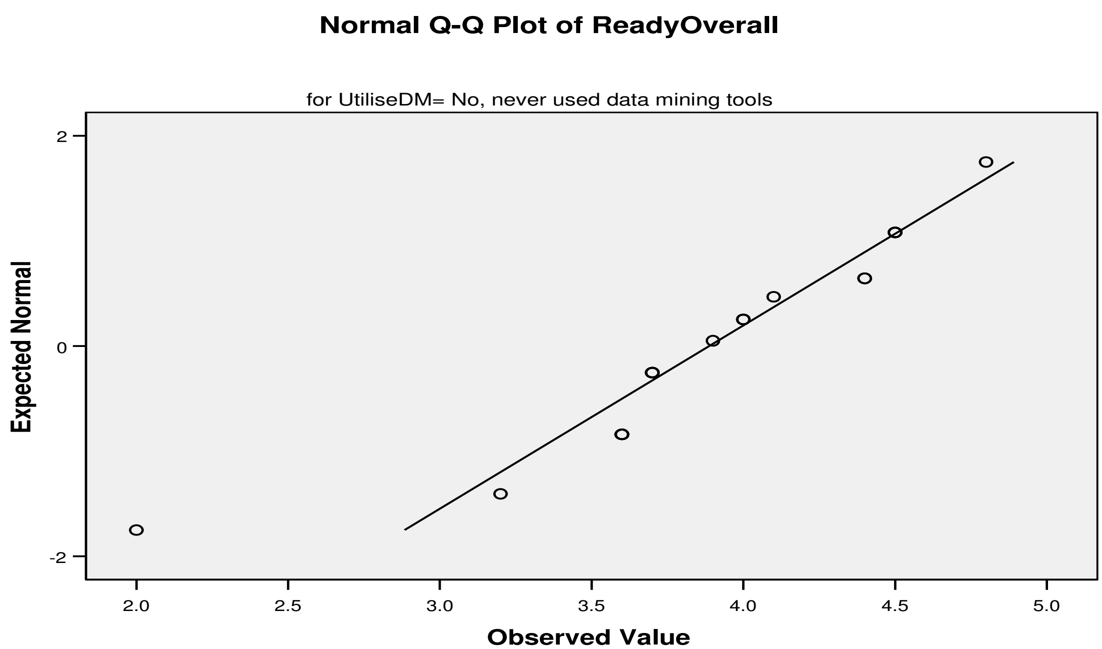
Table A6.2d: Test of Homogeneity of Variances: Adopter/Non adopter/Don't know (not aware)

ReadyOverall

Levene Statistic	df1	df2	Sig.
.049	2	127	.952

Figure A6.2d Result of test for normality





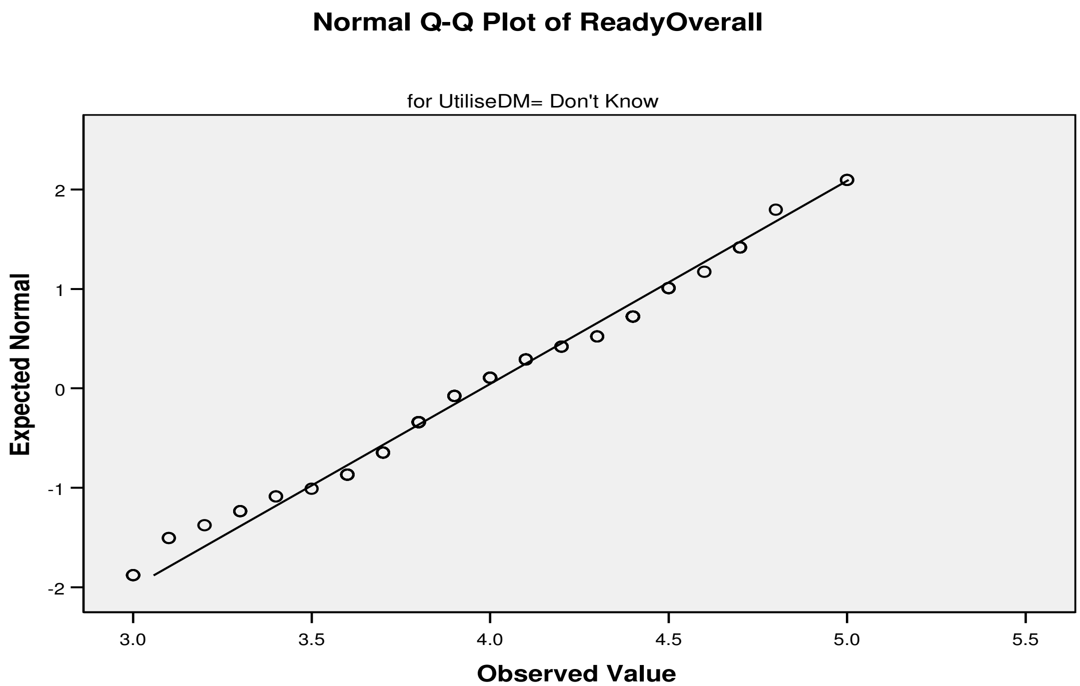
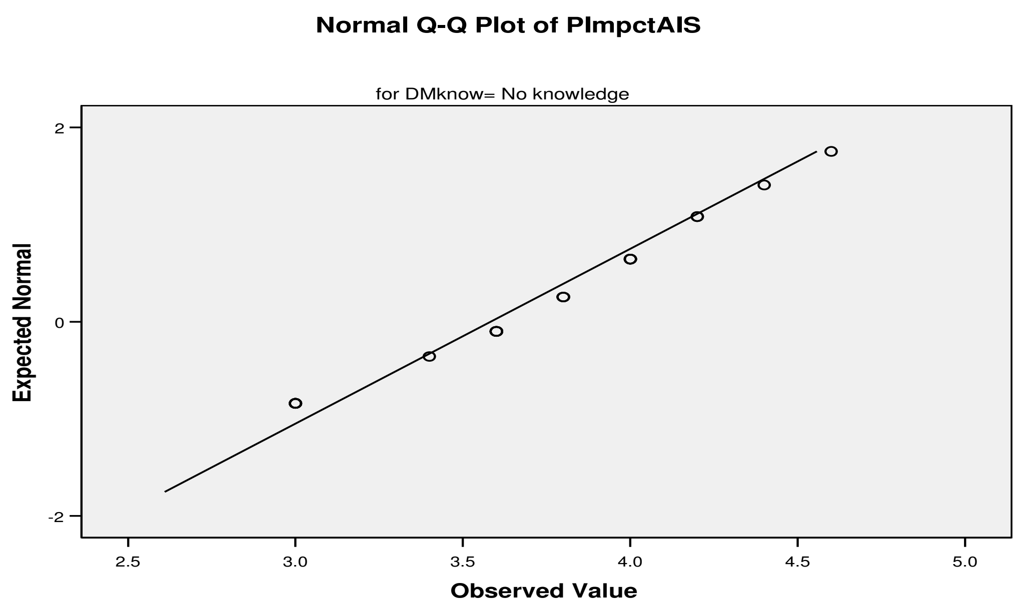
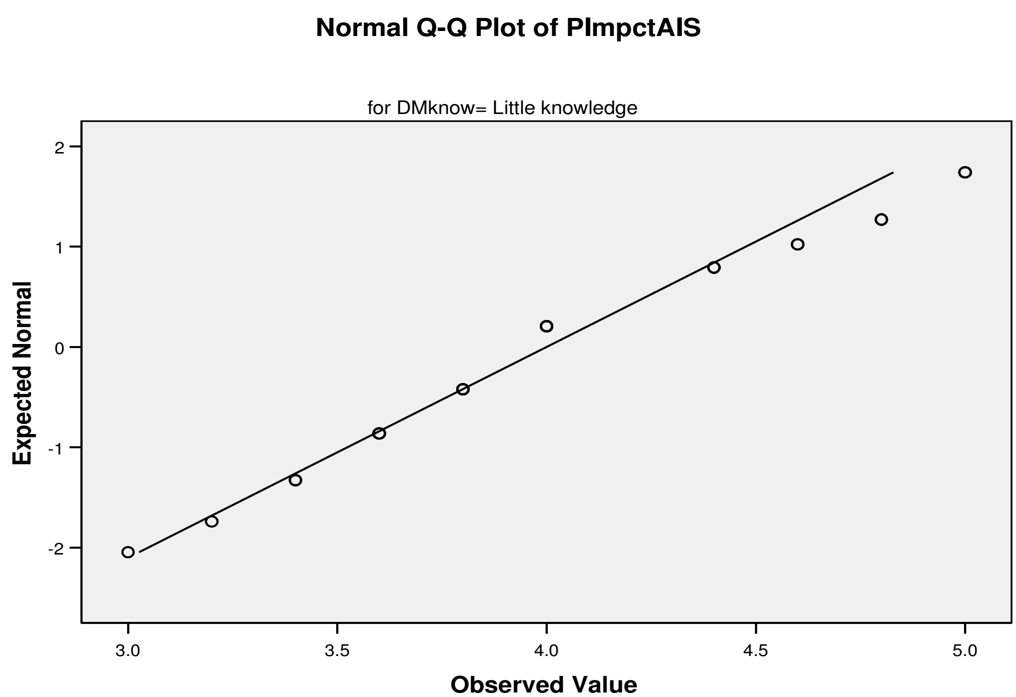

Normal Q-Q Plot of ReadyOverall
for UtiliseDM= Don't Know
Expected Normal
2
1
0
-1
-2
3.0
3.5
4.0
4.5
5.0
5.5
Observed Value

Table A6.2e:Test of Homogeneity of Variances: Data Mining Knowledge

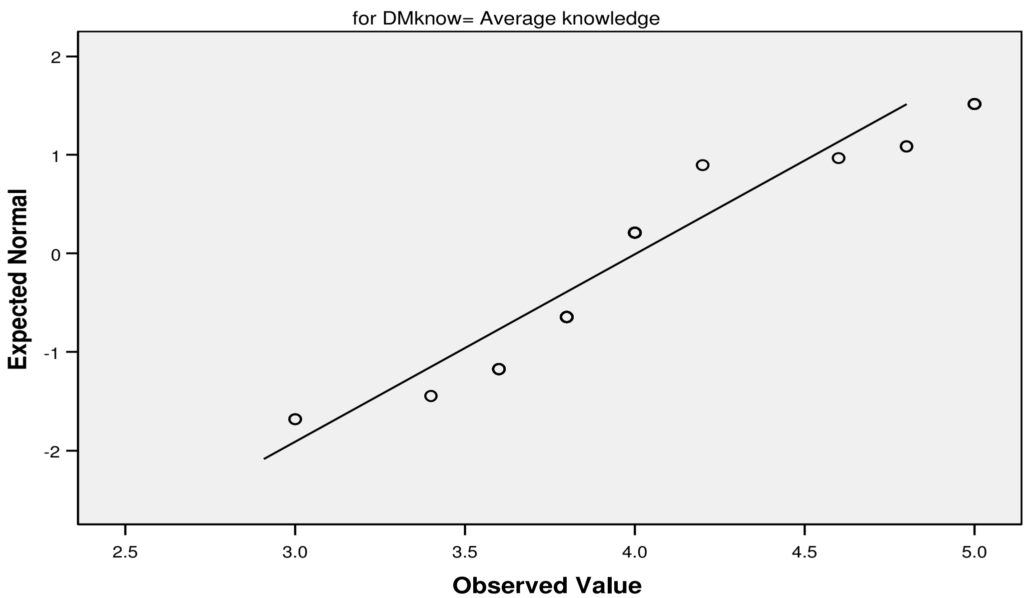
	Levene Statistic	df1	df2	Sig.
PImpctAIS	1.300	3	131	.277
PImpctDecM	.374	3	131	.772

Figure A6.2e Result of test for normality

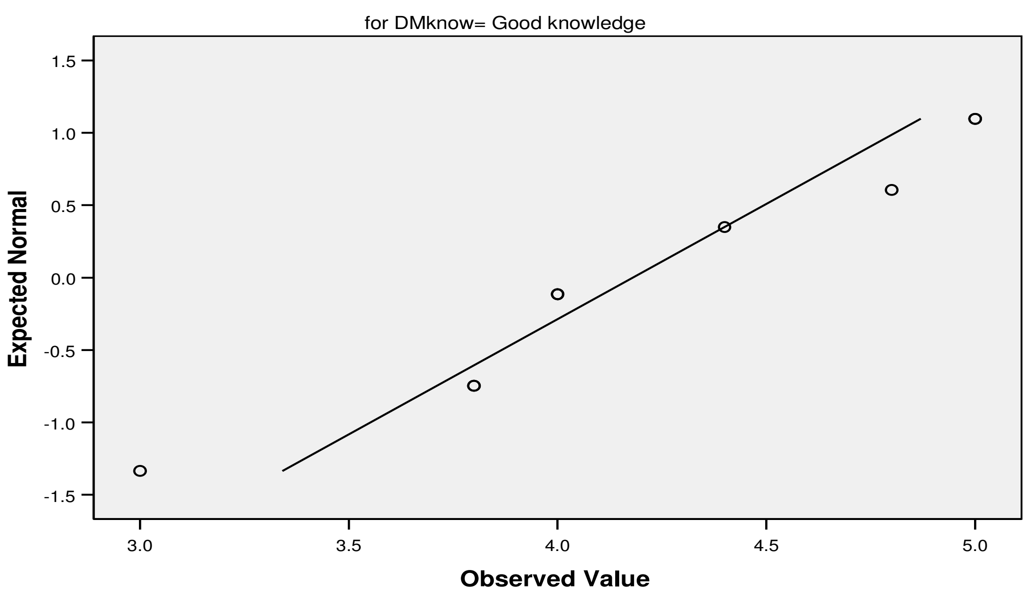




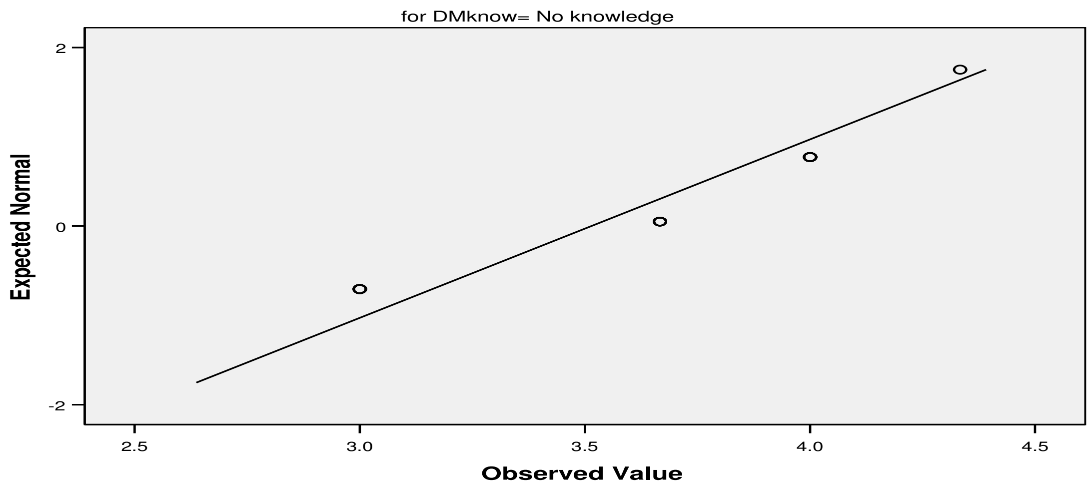
Normal Q-Q Plot of PImpctAIS



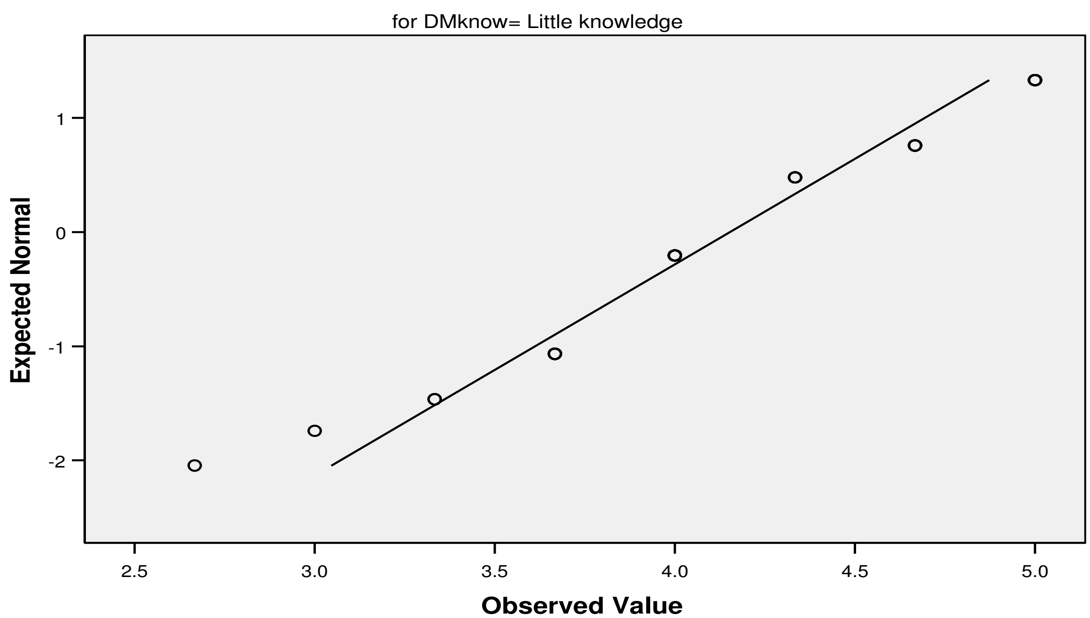
Normal Q-Q Plot of PImpctAIS



Normal Q-Q Plot of PImpctDecM

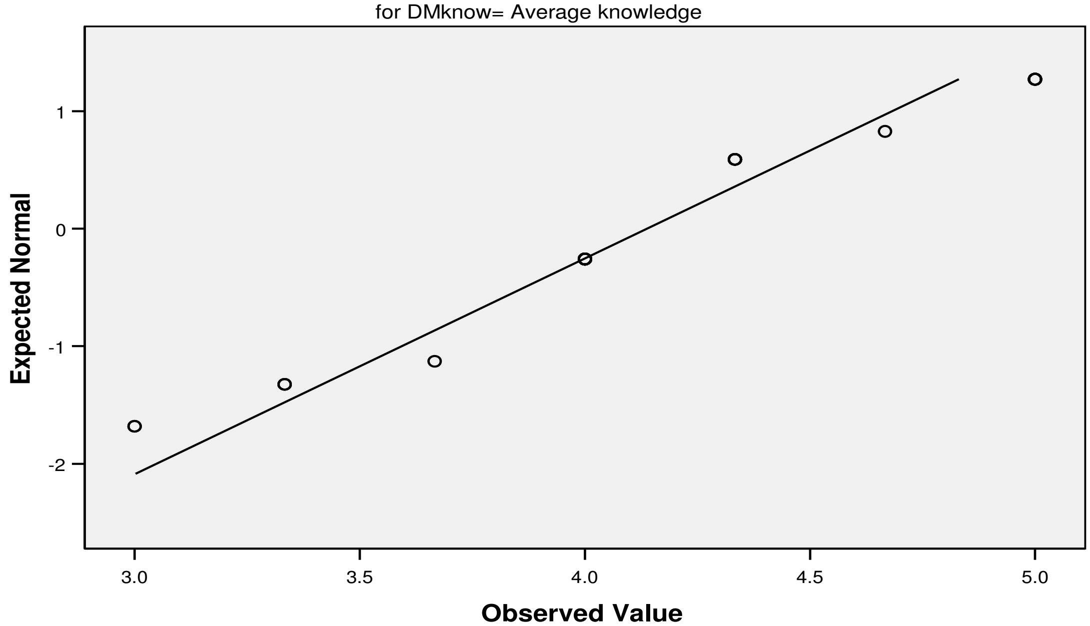


Normal Q-Q Plot of PImpctDecM



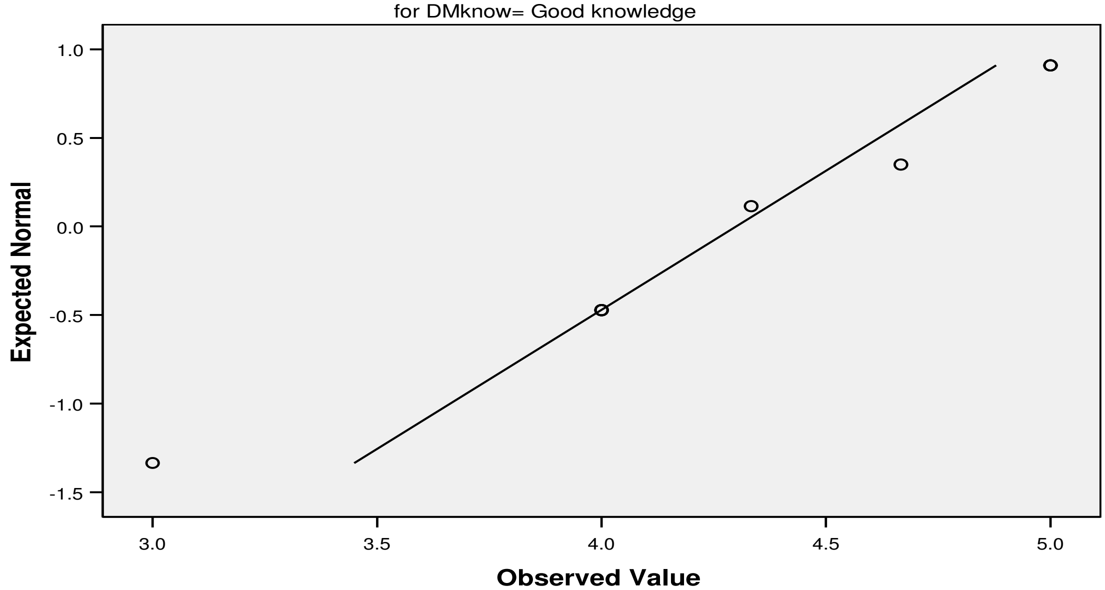
Normal Q-Q Plot of PImpctDecM

for DMknow= Average knowledge



Normal Q-Q Plot of PImpctDecM

for DMknow= Good knowledge



Appendix Seven: Reliability Statistics

Reliability Analysis: Technological Issues (Influence factors)

Item Statistics

Factors	Mean	Std. Deviation	N
11.1 Adequate technical support from vendors	4.1200	.66583	25
11.2 Compatibility of software with existing operating systems	4.2800	.73711	25
11.6 Up to date ICT infrastructure	4.3200	.69041	25

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
12.7200	2.877	1.69607	3

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance
Item Means	4.240	4.120	4.320	.200	1.049	.011

Inter-Item Correlation Matrix

	11.1	11.2	11.6
11.1	1.000	.693	.276
11.2	.693	1.000	.472
11.6	.276	.472	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
11.1	8.6000	1.500	.572	.483	.640
11.2	8.4400	1.173	.726	.565	.432
11.6	8.4000	1.667	.411	.227	.816

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.737	.735	3

Reliability Analysis: External Issues (Influence factors)

Item Statistics

	Mean	Std. Deviation	N
11.7 Changes in management trend within private sector	3.4800	.96264	25
11.8 Directives from politicians	2.8800	1.01325	25
11.9 In attempt to ensure public accountability	4.4800	.58595	25

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
10.8400	4.223	2.05508	3

Summary Item Statistics

	Mean	Minimum	Maximum	Range	Maximum / Minimum	Variance
Item Means	3.613	2.880	4.480	1.600	1.556	.653

Inter-Item Correlation Matrix

	11.7	11.8	11.9
11.7	1.000	.617	.313
11.8	.617	1.000	.312
11.9	.313	.312	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
11.7	7.3600	1.740	.613	.397	.425
11.8	7.9600	1.623	.609	.396	.435
11.9	6.3600	3.157	.347	.121	.762

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.684	.679	3

Appendix Eight: Association Analysis (Crosstab and Correlation)

a) Crosstabulation procedures between Knowledge about data mining and the intention to utilise data mining technology

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Intention to adopt DM * Please rank your knowledge about data mining?	73	52.9%	65	47.1%	138	100.0%

Intention to adopt DM * Please rank your knowledge about data mining? Crosstabulation

Count

Intention to adopt DM	Please rank your knowledge about data mining?				Total
	No knowledge	Little knowledge	Average knowledge	Good knowledge	
No Intention	0	1	2	0	3
Little intention	0	2	0	0	2
Moderate Intention	2	5	4	0	11
Definite Intention	1	21	28	7	57
Total	3	29	34	7	73

Symmetric Measures

		Value	Asymp. Std. Error(a)	Approx. T(b)	Approx. Sig.
Ordinal by Ordinal	Kendall's tau-b	.223	.095	2.200	.028
	Gamma	.462	.180	2.200	.028
	Spearman Correlation	.243	.105	2.110	.038(c)
Interval by Interval	Pearson's R	.180	.094	1.545	.127(c)
N of Valid Cases		73			

a Not assuming the null hypothesis.
b Using the asymptotic standard error assuming the null hypothesis.
c Based on normal approximation.

b) Correlation analysis between ability to utilise data mining and performance of AIS

Ability to utilise data mining vs Performance of AIS

		AbilityToUtiliseDM	AIS_Performance
AbilityToUtiliseDM	Pearson Correlation	1	.229(**)
	Sig. (2-tailed)		.009
	N	136	128
AIS_Performance	Pearson Correlation	.229(**)	1
	Sig. (2-tailed)	.009	
	N	128	130

** Correlation is significant at the 0.01 level (2-tailed).