The Determinants of the Adoption and Application of Business Intelligence: An ERP Perspective

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DECLARATION

I, Singha Chaveesuk, declare that the Ph.D. thesis entitled [The Determinants of the Adoption and Application of Business Intelligence: An ERP Perspective] is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

Signature…………………………… **Date** 21 September 2010

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ABSTRACT

Business intelligence, as a decision support tool in many organisations, has offered the ability to gather, store, access and analyse huge amounts of data so that better decisions can be made regarding customers, suppliers, employees, logistics and infrastructure. Prior empirical studies of business intelligence and decision support applications (BIDSA) focus on technological and operational aspects and there is very little research to consider managerial and strategic factors. The factors that affect the adoption of BIDSA have, however, not yet been fully investigated. Differences in the use of information technology (IT) have been distinguished in different countries and so it is necessary to conduct a comprehensive study about the facilitating and inhibiting factors in the adoption and diffusion of BIDSA in Australia. The aim of this study was thus to fill the gap by investigating factors affecting the successful adoption of BIDSA in Australian ERP user organisations by applying Rogers' theory of Diffusion of Innovations (DOI), and to develop a conceptual model for the successful adoption of BIDSA.

To investigate the factors affecting the adoption of BIDSA, this study develops models that are helpful in examining these factors. Questionnaire survey method was employed. Questionnaires were developed by applying the results of a preliminary study using interviews to collect data from the SAP Australian users, and literature and in the respect of innovation adoption. Primary data was gathered from the Enterprise Resource Planning (ERP) customers (approximately 450 SAP companies) in Australia. Statistical analysis methods and Structure Equation Modelling with AMOS were used to analyse and produce a suitable adoption model to show the relationship between the process of BIDSA adoption and factors from the conceptual framework.

The results show that the “BIDSA Adoption Models” (BIAM I and BIAM II) are useful in indicating factors affecting BIDSA and in distinguishing Australian organisations as early adopters and non-early adopters of BIDSA. The findings are in line with technological innovation theories that suggested that technological innovation, organizational and environmental factors were critical to stages of adoption. More importantly, for BIDSA adoption in Australia, organizational factors with regard to top management support and organizational size (resources) had a significant effect on their adoption of BIDSA. This research sees these factors as crucial and as an important aspect of BIDSA adoption.

According to the final modified research model, BIAM has the power to explain and predict successful adoption in related businesses. The study therefore contributes new knowledge and provides a better understanding of benefits regarding the use of BIDSA in Australian businesses as it is the first study to have empirically tested a model of BIDSA adoption in the context of ERP user organisations. The model can also provide guidance for Australian business organisations to evaluate and improve their use of BIDSA and, in addition, has important implications for top management and policy makers in developing the use of BIDSA as these stakeholders need to communicate effectively with their organisations about their BIDSA adoption intentions. Further investment in improving the decision support infrastructure and creating environments for developing the use of BIDSA is needed.

LIST OF ABBREVIATIONS

ABBREVIATIONS	FULL DISCRIPTION
AMOS	Analysis of Moment Structures
BI	Business Intelligence
BIDSA	Business Intelligence and Decision Support Application
CFA	Confirmation Factor Analysis
CBIS	computer-based information system
CRM	Customer Relationship Management
DSS	Decision Support System
DM	Data Mining
DW	Data Warehouse
EAI	Enterprise Application Integration
EIS	Executive Information System
ERP	Enterprise Resource Planning
ETL	Extraction-Transaction-Loading
GIS	Geographic Information System
ICT	Information and Communication Technology
IS	Information System
IT	Information Technology
KMS	Knowledge Management System
MIS	Management Information System
ODSS	Organizational Decision Support System
OLAP	On-line Analytical Processing
SAP	System Application Product
SCM	Supply Chain Management
SEM	Structural Equation Modelling

LIST OF GLOSSARY OF TERMS

Business Intelligence (BI)	The process incorporating technology by which businesses transform relatively meaningless data into useful, actionable information and then into knowledge.
Business Intelligence and Decision Support Application	A series of IT/IS/ICT applications designed to acquire knowledge for support of decision-making
Customer Relationship management (CRM)	An enterprise approach to understanding and influencing customer behaviour through meaningful communications in order to improve customer acquisition, customer retention, customer loyalty, and customer profitability.
Data Warehouse (DW)	The physical repository where relational data are specially organised to provide enterprise-wide, cleaned data in a standardised format.
Data Warehousing	The process of putting data into a relational database specifically organised to provide data for easy access.
Data Mining (DM)	A process that uses statistical, mathematical, artificial intelligence, and machine-learning techniques to extract and identify useful information and subsequently gain knowledge from large databases.
Decision Support System (DSS)	Computer-based information systems that are designed with the purpose of improving the process and outcome of decision-making.
Enterprise Application Integration (EAI)	An activity incorporating technology that integrates and harmonizes an enterprise's isolated business applications, process, and functions in order to provide common, sharable business applications,

	functions and services within the enterprises.
Enterprise Resource Planning (ERP)	A packaged enterprise-wide information system that integrates all necessary business functions (e.g. product planning, purchasing, inventory control, sales) into a single system with a shared database.
Extraction-Transaction-Loading (ETL)	Tools that are pieces of software responsible for the extraction of data from several sources; their cleansing, customization, and insertion into data warehouse.
Executive Information System (EIS)	A computerised system that provides executives with easy on-line access to internal and external information relevant to their success factors.
Knowledge Management System (KMS)	IT based systems developed to support and enhance the organisational processes of knowledge creation, storage/retrieval, transfer, and application, and are manifested in a variety of implementations.
On-line Analytical Processing (OLAP)	An information technology technique that mainly refers to versatile analyses of data and presentation of data.
Supply Chain Management (SCM)	The systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole.
IT*/IS/ICT*** **	A broad subject concerned with technology and other aspects of managing and processing information dealing with the use of electronic computers and computer software to convert, store, protect, process, transmit, and retrieve information to achieve effectively.

*Information technology
**Information System
***Information Communication Technology

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Organisational survival can depend on integration of information provided by various information systems (IS) (Ashrafi et al. 2006). Many organisations have evolved can abundance of information but cannot make best use of it, even through efforts to improve use of decision support tools (Evans & Wurster 1999). Due to the growing need to analyse large amounts of complex information, many enterprises' traditional decision support application tools have become incapable of effectively handling the demand for timely and quality information. This inability makes it difficult for management to utilise and understand information efficiently and effectively (Gar-On Yeh, Kersten & Mikolajuk 1999; Gray & Watson 1998). It is thus important to seek ways and means to combine, access, store, and analyse the massive amount of data and to provide queries and complex reports and competitive information simply to decision makers.

As IS has become an attractive means of improving these processes, organisations have implemented several strategies to improve effectiveness and to enhance efficiencies through the use of information technology (IT). Until recently, one of the possibilities for providing such an analytical tool was to adopt business intelligence (BI) technology which Golfarelli, Rizzi & Cella (2004) describe as "turning data into information and then into knowledge". Knowledge is typically captured about customer needs, decision making processes, the competition, conditions in the industry, and general economic, technological, and cultural trends. The main application of BI is to perform data gathering, data storage, and data analysis in order to better understand the situation of the business and to improve the decision process. For example, data warehouse (DW), on-line analytical processing (OLAP), data mining (DM), and BI real-time capabilities can be a useful way to combine and query various data and to provide knowledge with insightful analysis to match users' demands.

A study by Lyman & Varian (2000) found that the world produces between 635,000 and 2.12 million terabytes of unique information per year, most of which has been stored in servers or databases. Many IT devices serve as the repository, supporting convenient access to information, but also posing challenges for obtaining effective information from voluminous data. With large amounts of complex data consisting of structured data and semi-structured data, it has been suggested that BI is an appropriate tool to deal with this (Moss 2003; Rudin & Cressy 2003). A survey found that 60% of chief information officers (CIOs) consider semi-structured data as critical for improving operations and creating better decision processes (Blumberg & Atre 2003a), but semi-structured data is not easy to query using conventional databases and tools (Blumberg & Atre 2003b). Blumberg & Atre (2003a) indicated that more than 85% of all business information exists as semi-structured data in any one company. However, managing semi-structured data still persists as a major unsolved problem in many enterprises (Blumberg & Atre 2003a). Thus, to create business intelligence information, the integrated data (knowledge) are useful for decision makers and the specific tools (e.g. data warehouse, OLAP, data mining) are currently used by many companies to deal with both structured and semi-structured data.

Whiting (2003) noted that demand for BI applications continues to blossom even at a time when demand for most IT products is slowing down. Negash & Gray (2003) reported that BI represents the biggest current growth area in information technology investment in many enterprises. During 2003-2006, the rate of growth of BI solutions was significant and was one of the fastest at around US$ 12 billion with 23% annual growth rate (Darrow 2003; Giang 2002). BI technology plays an important role in many companies using a large amount of data. Foster, Hawking & Stein (2005) pointed out that BI is often found in organisations using enterprise-wide applications such as enterprise resource planning (ERP) systems. It is suggested that BI technology provides information (knowledge) to enhance decision making in an ERP organisation (Hawking, Foster & Stein 2008).

As business intelligence (BI) provides an alternative analytical solution that extends decision support capabilities, it assists decision makers to identify relationships among data items so potentially enhancing understanding and providing competitive advantage. There are numerous examples of benefits in achieving its objectives that an enterprise can gain by utilising BI (Thomas Jr. 2001). Watson et al. (2006) reported that BI is significant because of its potential for affecting tactical decision making and business processes (e.g. Continental Airlines is a leader in real-time business intelligence and accomplished in their businesses). In particular, it can also provide information to enable costs to be cut, stronger customer linkages to be created, to innovate, and to plan (Hannula & Pirttimaki 2003). Therefore, the IT used in analysing the data and storing and reporting intelligence is also considered an important part of BI (Moss & Atre 2003).

1.2 RESEARCH PROBLEM

In modern organisations, information is abundant however the problem for decision makers is not finding information, but selecting appropriate information is more important (Davenport & Beck 2001). Despite the trend of business intelligence (BI) increasing worldwide, given the opportunities and benefits that BI can provide to major businesses, there is often a gap in a developed country in the use of business intelligence and decision support applications.

Significant spatial inequalities still persist in the use and adoption of information communication technologies (ICTs) (VanDijk 2005), not only between developed and developing countries, but even within industrialized countries (Rallet & Rochelandet 2007). Recent evidence has been provided for differences of using ICTs, for instance, with reference to the United States (Greenstein & Prince 2006), Australia (Willis & Tranter 2006) or Europe (Demoussis & Giannakopoulos 2006). Thus, it has been acknowledged that BIDSA inequalities exist among regions and in some cases they are larger and more persistent than differences among countries.

This gives a geographical point of view about the variation of ICT appropriation among various regions by analysing the spatial aspects of their diffusion. Dewan & Kraemer (2000) found that Australia could be rated as a “straggler”, falling behind other developed countries such as New Zealand, Sweden, UK, Canada, Japan, Belgium, Denmark, Israel, Finland, and U.S.A. Previous research mentioned that investment in IT is identified as the most critical but difficult management issue in Australia (Pervan 1997). It has been suggested that Australian businesses are relatively slow in adopting the technology as shown in a study of countries investing and adopting BI solutions (Foster, Hawking & Stein 2005).

According to these surveys, it is estimated that 95% of the Fortune companies in the U.S. (META Group 1996) and 85% of top European companies ('Clear targets vital for data warehousing' 1996) have a data warehouse in place, but approximately only 50% of firms with ERP systems in Australia have one (Foster, Hawking & Stein 2005). Enterprise using

ERP systems are significant contributors to information technology (IT) usage and the economy in Australia (BRW 2002; Kummar, Maheshwari & Kumar 2002). Further, in another perspective of BI systems used, a survey revealed that more than 60% of companies owning a BI application rated the system as having limited implementation (Stedman 1998). In addition, the level of decision support available to foster better decision making in organisations with ERP systems can, however be questioned (Holsapple & Sena 2003; Wah 2000).

This study will begin by investigating business intelligence in those Australian companies making use of ERP systems (I will refer to these companies as ERP enterprises). Although an ERP systems' strength is the integration of data across functional areas (e.g. marketing, finance and accounting, logistics and production) to support particular business processes, the capability of effective decision making and BI technology has been limited (Davenport, Harris & Cantrell 2004; Moller 2005).

Unfortunately in the area of adoption of BI technology, most of the available research focuses on technological and operational aspects (Arnott & Pervan 2005; Foster, Hawking & Stein 2005; Gibson & Arnott 2003; Hawking, Foster & Stein 2008; Rudra & Yeo 1999; William & William 2003) and there is very little research to consider human, managerial, and strategic factors. Previous research indicated that many organisations have poor IS/IT adoption practices (Fink 1998). In addition, there is little research that studies the key factors affecting adoption of BI technology, especially for enterprises in Australia. Even though many ERP companies have an interest in establishing BI solutions, a lack of academic research limits the understanding of its individual and organisational implications (Watson & Wixom 1998;

Wixom & Watson 2001). More systematic study is necessary to gain an in-depth understanding of the business implications and to justify future system investment.

This study aimed to build a model to investigate the factors affecting the successful adoption of BI. This research focuses on BI technology from a variety of ERP user organizations in Australia. Even among the limited literature on the adoption and diffusion of BI solutions there is a scarcity of studies on the empirical perspectives of BI solutions.

1.3 JUSTIFICATION FOR THE RESEARCH

As mentioned, there is a gap in some developed countries in the use of business intelligence and decision support applications in improving business decisions and enhancing decision-making. Based on assessment of previous studies, it was found that the factors that affect the adoption of business intelligence and decision support applications (BIDSA) by Australian business organisations have not yet been fully investigated (see Chapter 2). The little study that was identified provided some insights but not a comprehensive range of these factors.

In Australia, Foster, Hawking & Stein (2005) studied the adoption of BI in ERP firms, but they focused only on technological and operational innovations and the use of BI in each ERP user firm. Hawking, Foster & Stein (2008) studied the adoption and the use of business intelligence solutions in terms of an evolutionary maturity to how BI solutions are adopted in Australian companies.

No research was found that studied aspects of the strategic factors affecting the adoption of business intelligence and decision support applications (BIDSA). Thus, this study attempts to bridge this gap by exploring factors affecting the adoption of BIDSA of Australian businesses.

1.4 AIMS OF RESEARCH

The general aim of the research was to explore factors affecting the adoption of business intelligence and decision support applications in business organisations in Australia. However, the specific aims were:

1.4.1 To examine the adoption, implementation and diffusion of business intelligence and decision support applications (BIDSA) by Australian organizations in terms of company characteristics

1.4.2 To investigate the facilitating and inhibiting factors affecting the adoption of BIDSA in Australian organizations

1.4.3 To develop a model for the successful adoption and diffusion of BIDSA by ERP organisations in Australia

The aims of this study are translated into the three following research questions:

1. How do the company characteristics differ in the extent of adoption and implementation of BIDSA by Australian organizations?

   (This question is formulated from research aims 1.4.1)

2. What are the potential factors affecting the adoption of BIDSA by ERP user firms in Australia? If there is a difference, in what kind of specific factors do the adoption and implementations of BIDSA differ from early adoption and non early adoption?

   (This question is formulated from research aims 1.4.2 and 1.4.3)

3. Which factors are the most important in the promoting/inhibiting of BIDSA?

(This question is formulated from research aims 1.4.2 and 1.4.3)

4. Does this proposed model adequately describe previously successful adoption of BIDSA? And can it be used to predict future adoption of BIDSA?

   (This question is formulated from research aims 1.4.2 and 1.4.3)

In attempting to answer all research questions, this study formulates a theoretical model based on the classical innovation diffusion theory (Rogers 1995). An important innovation within business intelligence and decision support applications (BIDSA) functions is the use of information technology (IT), and this initial adoption decision framework is used to depict what factors affect the adoption of business intelligence and decision support applications in Australian organisations. The model proposed will be presented in Chapter 3.

1.5 CONTRIBUTION OF THE RESEARCH TO KNOWLEDGE

Business intelligence (BI) has become a worldwide trend, and the evaluation of current factors assists in clarifying relationships with the decision support processes and technological characteristics. This research is an exploratory study on the adoption of business intelligence and decision support applications (BIDSA) in Australian ERP user organisations. In fact, this study is very important for identifying and highlighting the factors affecting the successful adoption of BIDSA for Australian managements and also worldwide.

The research will provide a better understanding of, and important insight into the key factors influencing the use of business intelligence and decision support applications (BIDSA) in Australian firms. The results will help ERP managers and top management in Australia to improve their business decision processes for enhancing better decision-making.

In particular, this study will contribute to knowledge about the successful adoption of business intelligence and decision support applications (BIDSA) by IT and business areas for both practitioners and academic researchers as follows:

1. Little empirical evidence has been published on the use of business intelligence in Australia. This study will fill a knowledge gap about the use of business intelligence by business organisations in Australia.
2. This study is based on innovation diffusion theory, which has been used widely in information systems innovation research. This study focuses on decision support activities in two different stages related to the diffusion of innovations: the early adopters and non-early adopters. Little comparative research has been conducted on BIDSA in different stages of adoption. It will provide other researchers with another example of the use of this theory to study innovation factors relating to business intelligence and decision support applications (BIDSA).
3. The model developed by the study will be used to investigate previous adoptions and to isolate factors that are likely to lead to future successful adoptions. The study should contribute significantly to the global understanding of innovation adoption through the development of the research model in an Australian innovative context. This study presents the specifically powerful "Business Intelligence and Decision Support Applications Model" using actual usage and intention to use the BIDSA technology by testing and verifying the theoretical framework along with practical applications in the environment of the ERP users. A major contribution to the existing knowledge and literature is the application of structural equation modelling (SEM). The application of SEM promotes a better quality of research relating to adoption and diffusion in an innovative context. SEM has useful features particularly in modelling

multivariate relations, and there are no widely and easily applied alternative methods of this kind (Byrne 2006).

1.6 SIGNIFICANCE OF THE STUDY

This study identifies the benefits of adopting business intelligence and decision support applications (BIDSA) for business organisations in Australia:

1. The research extends knowledge about analytical tools in business organisations and fills a knowledge gap about the adoption of BIDSA that will give management a better understanding of this innovation and develop more positive attitudes and be more receptive towards adoption and implementation of BIDSA.
2. Such knowledge will be useful for a policy maker (top management) in being encouraged to become more proactive in promoting the adoption of BIDSA to increase the chances of success in business decisions in order to improve productivity and increase competitiveness.
3. This research has applied a theoretical framework from innovation theory to model the technological adoption of BIDSA. This will provide additional useful material to those wishing to undertake academic research in the adoption and diffusion of innovations.

1.7 SCOPE OF THE STUDY

This study involved qualitative as initial stage and following by quantitative methods to investigate factors affecting the adoption of business intelligence and decision support applications (BIDSA) in Australian business organisations. This study focused on ERP user organizations in Australia. The senior manager; for example the chief information officer

(CIO), IT project managers, or senior IT managers, who should also be a decision maker in relation to the business decision support activities, were the key informants of the study.

1.8 ORGANISATION OF THE THESIS

This thesis is organised into SEVEN chapters as follows:

1. **Chapter 1** introduces the background information identifying the research problem, the purpose of the research, and its contribution to knowledge.
2. **Chapter 2** reviews the existing relevant organisational, technological innovation adoption and decision support technology literature to provide the theoretical foundation for the proposed conceptual model.
3. **Chapter 3** indicates the development of the conceptual model, and related research questions and hypotheses are presented.
4. **Chapter 4** describes the methodology used to empirically test the conceptual model in the study, quantitative methods, development of the research instruments, the tests for validity and reliability of the research instruments, as well as ethical considerations. The selection of participants, data collection methods and the statistical techniques for data analysis are also discussed in this chapter.
5. **Chapter 5** reports the results of the preliminary data analysis, using a quantitative survey of ERP user organization undertaken in Australia and reports the initial findings from these including reliability and validity analysis, response rates, the extent to which business intelligence and decision support applications (BIDSA) have been adopted and used, and respondents' characteristics.
6. **Chapter 6** involves the main data analysis related to testing and developing the model of innovation adoption called the "BIDSA adoption model (BIAM)" by utilising multivariate analysis using structural equation modelling (SEM).

7. **Chapter 7** provides a discussion and conclusion of the quantitative findings. The limitations of the study and theoretical and practical implications for Australian organisations are discussed. Finally, recommendations for further research are also suggested in this chapter.

1.9 SUMMARY

This chapter has provided an introduction to the issues that this research has been designed to address. The research topics were organised as: 1) The research background; 2) research problem; 3) research aim; 4) research questions; 5) main area of the study and the significance of the study; and 6) the scope of the thesis, the outline of the thesis, and definitions. The next chapter will present a review of literature, as well as the theoretical model for this study.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Business intelligence (BI) is a major component of many organisation's IT portfolio, however the area is significantly under researched (Arnott & Pervan 2005). Despite the increasing importance of the use of BI as a decision support technology in high information usage business organisations, the factors that affect the adoption of BI and decision support applications (BIDSA) by business organisation have not yet been fully investigated (Arnott & Pervan 2005; Foster, Hawking & Stein 2005; Gibson & Arnott 2003; Hawking, Foster & Stein 2008). In this study, the focus is on the adoption of BIDSA in Australia, based on an ERP perspective. This chapter will provide the theoretical concepts for developing information analysis and organisational innovations, and use them for presenting a model (see Chapter 3) for evaluating the factors affecting adoption of BIDSA by a business sector in Australia.

2.2 THE NEEDS FOR BUSINESS INTELLIGENCE

Thousands of companies around the world have implemented ERP (Rajagopal 2002). A review of the literature suggested that ERP has been used by small, medium, and large enterprises including government agencies as research has focused on the competitive advantage of ERP and the importance of considering a business model and core competencies when making decisions for or against ERP implementation (Davenport 1998; Lengnick-Hall, Lengnick-Hall & Abdinnour-Helm 2004; Prahalad & Krishan 1999). Prior researchers have reported that ERP allows a company to manage its business data analysis better and provide higher quality data for decision-making (Fan, Stalert & Whinston 2000; Gattiker & Goodhue 2005; Lengnick-Hall, Lengnick-Hall & Abdinnour-Helm 2004; Zheng, Yen & Tarn 2000). Many firms expect that enterprise resource planning (ERP[1]) can be used to support automating business process, timely access to management information, and assisting in decision-making (Li, Liao & Lei 2006; Umble, Haft & Umble 2003).

Suggested by Davenport (1998), the "need to make timely business decisions" is seen as a major reason for ERP implementation, however ERP does not seem to provide for the need to distribute the analytic capability to various operational levels, targeted at specific business needs via key performance indicators (KPIs), dynamic reporting and real-time analytics (Agostino 2004; Chou, Tripuramallu & Chou 2005). From prior research, Holsapple & Sena (2003) suggested that from their research, ERP adopters perceive that decision-support characteristics are exhibited to a "moderate" degree by their systems. Most enterprises having implemented ERP are implementing, planning or considering various extensions to the system, however an empirical study by Olhager & Selldin (2003) showed that a majority of enterprises were not even considering business intelligence capabilities.

This means that most enterprise using ERP systems have traditionally been concerned with managing the processing of business transactions rather than business intelligence using its components. Also, Holsapple & Sena (2005) reported that no study has examined ERP functioning as a type of organisational decision support systems (ODSS)[2]. It is implied that there is need for decision support in ERP, and that decision support characteristics can be

[1] Al-Mudimigh, Zairi & Al-Mashari (2001) define an ERP as "a packaged enterprise-wide information system that integrates all necessary business functions (e.g. product planning, purchasing, inventory control, sales) into a single system with a shared database".
[2] Carter et al. (1992) define an ODSS as "a common set of tools used by multiple participants from more than one organisational unit who make interrelated, but autonomous decisions".

exhibited by ERP implementations, but that organisation does not realise the decision-support benefits from ERP.

As ERP has been accepted, companies investigate avenues for achieving strategic value from the additional functionality available in the system as seen in the model by Holland & Light (2001). It can be suggested that the need of data distribution across the firm boundary is extensively increasing and analytical functions are no longer able to provide this within the organization. The model focuses on firms moving from core ERP transactions to enterprise application integration (EAI) to integrate and collaborate with business partners. This implies increased reliance on BI solutions as ERP with BI infrastructure (e.g. data warehouse[3]) have become major players in the business intelligence market (Chou, Tripuramallu & Chou 2005; Foster, Hawking & Stein 2005).

With the demand to manage high volumes of data in an enterprise, BI technology has the potential to generate "actionable knowledge" or in-depth analytical information (Gupta & Sharma 2004). Prior research by Li (1999) has identified the need to generate BI as a primary key to provide decision support characteristics to ERP. It can be seen that while many organisations recognise the wealth of information within ERP systems, the challenge still lies in the ways of mining them. These include the provision of a repository of knowledge for solving problems and mechanisms to facilitate communication within an organisation. For example, in reporting capability ERP does not offer reporting service on product line revenue analysis. It is not capable of providing an ad hoc reporting service. Another weakness of

[3] Turban, Aronson & Liang (2005) define data warehouse (DW) as "the physical repository where relational data are specially organised to provide enterprise-wide, cleaned data in a standardised format".

ERP is the limitation of integration capability with other systems. CRM[4] and sales force automation systems' forecasting capability could be used to empower business decision if they can be integrated with ERP. Also, the budgeting tools are often well integrated with ERP, which causes concerns on financial data consistency.

To justify the return-on-investment (ROI) in firms, many organisations are turning to BI tools that use data sources from ERP, customer relationship management (CRM), supply chain management (SCM[5]), and other external data. BI systems can pull the data from them then perform various analyses and deliver superior reporting which helps users make timely and accurate decisions (Kumar & Hillegersberg 2000).

For example, the banking industry is today more oriented towards selling new products than toward traditional services such as offering loans and holding deposits. BI in the financial industry becomes a crucial technology in support of strategic goals (Curko, Bach & Radonic 2007). To avoid the risk typically applied to the financial industry, it is important to accurately estimate probability of default prior to issuing of a loan. Specific business modelling (Credit and Behavioural Scoring) with a BI tool has become the useful tool to model financial problems. Beyond simply understanding customer value, the bank can gain the opportunities to generate better customer loyalty and revenue (Hsieh 2004). Moreover, products and offers are created to be more appealing to various customer segments. Large amounts of data about their client banks can be used for analysis of customer behavioural features. Data jointly with customer satisfaction survey data acquired from CRM can be

[4] Swift (2001) defines a CRM as "an enterprise approach to understanding and influencing customer behaviour through meaningful communications in order to improve customer acquisition, customer retention, customer loyalty, and customer profitability.

[5] Mentzer et al. (2001) defines a SCM as "the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole"

successfully mined to segment profitable customers (Lee & Park 2005). The BI technology can detect new, previously unknown, customer segments, which can then be targeted with the bank's specialized offerings. This enhances the traditional segmentation approach and augments the bank's profitability.

In the retail business, the major area of benefit from BI tools (e.g. data mining[6]) is in the area of market basket analysis (Bigus 1996). This analysis is to understand the association structure between the sales of the different products available (Chen et al. 2005). For example, if there is a relationship between two products over times, then retailers can use this information to contact the customer, decreasing the chance that the customer will purchase the product from a competitor.

Armed with timely and accurate information, the most current IT is to congregate all needed data from (e.g. ERP, CRM, SCM) and then load them into the data warehouse or a data mart which can be useful to structure the information, leading to an increased interest in analysing and using the accumulated historical data, while BI tools (e.g. on-line analytical processing (OLAP[7]), data mining, query, and reporting) provide insight into data through fast, consistent, interactive access to a wide variety of possible views of information that has been transformed from raw data to reflect the real dimensionality of the enterprise as understood by users. Prior research by Negash (2004) and Olszak & Ziemba (2004) suggested that BI contributes value to business sectors by:

[6] Turban, Aronson & Liang (2005) defines a data mining as "the process that use statistical, mathematical, artificial intelligence, and machine-learning techniques to extract and identify useful information and subsequently gain knowledge from large databases.

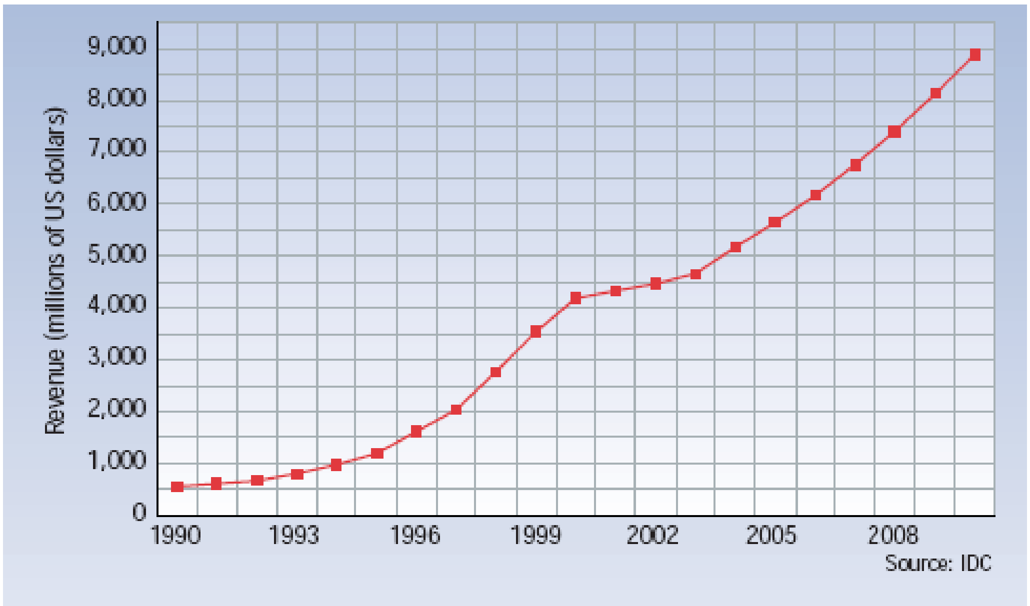
[7] An OLAP is defined as "an information technology technique that mainly refers to versatile analyses of data and presentation of data" (Kalakota & Robinson 1999; OLAP Council 1997).

- Providing meaningful analyses. BI performing OLAP and data mining tools to discover meaningful trends and particular patterns. For instance, these tools can obtain more detailed information to generate best- or-worst case scenarios for business planning.
- Optimising the operation system investment so that an organisation can better gain its competitive advantage. For example, a BI solution might allow purchasing personnel to discover patterns in pricing, which in turn allows the firms to acquire better pricing by changing the purchasing process.

Under these circumstances, more and more organisations extend their enterprise systems beyond the level of back-office (e.g. ERP, CRM, SCM) to improve sales, customer satisfaction, and business decision-making (Hawking, Foster & Stein 2008; Tern, Yen & Beaumont 2002; Willis & Willis-Brown 2002). This is because these transactional systems do not meet management's need to discover trends and patterns that can be derived from their inherent business rules. These discoveries are then used to enhance organisations (Shang & Seddon 2000; Zeng, Chiang & Yen 2003) as BI can control the vast stocks of data and flow of business information within the organization by first identifying and then processing the information into condensed and useful managerial knowledge and intelligence.

Consequently, it has been expected that BI technology would lead to innovation in business information and decision-making, and be considered to be one of the key drivers of corporate success (Cardozo et al. 1993; William & William 2003). While using BI, decision makers are moved to the next stage by providing them with better understanding of a firm's operations so that they can outmanoeuvre competition and make better decisions whether tactical, strategic, operational or financial (Thierauf 2001). The continuing improvements and the rising use of these advanced information systems help people to acquire meaningful information for easy use. According to Gartner (2008), chief information officers (CIOs) are coming under increasing pressure to invest in technologies that drive business transformation and strategic change. In addition, innovation and growth rate arising from technologies can make it easier to build and consume BI applications. It is implied that BI is needed as a decision support function and vital to any company. Figure 2-1 also reported by marketing firm IDC suggests that BI application demands will increase at a faster rate than during the previous 15 years.

As many organisations are faced with unprecedented growth in the sheer amount of data available from legacy systems (e.g. ERP, CRM, SCM) to them, organisations create information systems to deal with business requirements as these develop, often leading to many disparate systems. With regards to the important application of BI technologies, BI plays a critical role in providing actionable information to enable better business decision-making. As BI systems combine data-gathering, data storage and knowledge management with analytical tools to present complex internal and competitive information to planners and decision-makers, BI is an important approach to decision support.



Source: Lawton (2006)

Figure 2-1: Market research predicts that the demand of BI applications is increasing

2.3 THE IMPACT OF BI

Many expect that BI is used to generate various aspects of business views for supporting and analysing accurate and timely information to increase the company's performance (Gangadharan & Swami 2004). Moreover, BI leads to improved financial, strategic operational or information risk by enabling decision makers to see changes in the underlying business as fast as possible (Ericsson 2004). As a result, BI is capable of leveraging the company's assets to optimize their value and provide a good return on investment (ROI) (Thierauf 2001). Initially, BI is an important strategic tool intended to help with planning and performance measurement rather than with purely operational decisions (Rouibah & Ould-ali 2002). Prior research reported that by utilising the model to assess BI performance, 24% improvement in effectiveness has been achieved in terms of system effectiveness and user satisfaction (Lin et al. 2008). Moreover, BI has the potential to offer decision makers a better perspective compared to analysis by conventional methods in many situations.

For example, as pointed out by Olszak (2002), BI also provides adequate and reliable up-to-date information on different aspects of enterprise activities. A variety of companies including retailers, telecommunications providers, travel agencies, and manufacturers use BI for various activity purposes such as customer profiling, customer support, market research and segmentation, product profitability, statistical analysis, and inventory and distribution analysis (Olszak & Ziemba 2004).

Particularly in the retail industry, as researched by Ranjan & Khalil (2008), BI is becoming necessary at the present time for the retail sector in India and is widely accepted for modern and advanced decision support tools. As such, the retail giant Shopper's Stop in India is trying to upgrade its business strategies using these particular systems. It could be believed that BI systems provide good impacts to companies in: 1) stabilising the decision-making process; and 2) increasing the visibility of company information to stakeholders. Regarding this, Cunningham, Song & Chen (2004) showed significantly that a BI (e.g. data warehouse) supports CRM analyses by providing various profitability analyses (e.g. customer profitability analysis, market profitability analysis, product profitability analysis, and channel profitability analysis).

Moreover, as described by Nguyen Manh, Schiefer & Tjoa (2005), Sahay & Ranjan (2008), and Viitanen & Pirttimaki (2006), the development of a decision support information system such as a BI decision support function is critical to successful decision-making in seeking to reduce data latency (near real-time). It is important because not only is it the analysis done on near real-time data, but also actions in response to analysis results can be performed in near real-time, and instantaneously change parameters of business process (Azvine, Cui & Nauck 2005).

As ERP has grown fast in automating back office operations and become an important infrastructure for many organisations (Hannula & Pirttimaki 2003), it is clear that today's companies are more process-oriented than in the past and process-driven decision support systems are emerging to help enterprises improve the speed and effectiveness of business operations with the ability of data-driven decision-making (Baïna, Tata & Benali 2003). Like other industries, several players implementing ERP have used BI as a potential analytic technology to extend decision support capabilities, and to generate various aspects of business views through manipulating existing data from different sources of each functional application captured by the company's information systems (Chou, Tripuramallu & Chou 2005).

Since ERP includes the entire range of a company's activities and integrates all facets of the business, including planning, marketing, and manufacturing (Shehab et al. 2004), BI has elements or processes incorporating related technologies for transaction-based systems[8] (Foster, Hawking & Stein 2005; Hawking, Foster & Stein 2008). Thomas Jr. (2001) suggested that BI has had a significant impact on different functions (e.g. marketing, finance, production, etc.) in high IT and information usage industries including the ERP industry. In particular, Abukari & Jog (2002) pointed out that firms use BI in a number of ways to seek competitive advantage including the following:

- Analysing sales trend and patterns, customer profitability and product profitability. This includes demographic-based response modelling for product offers and

[8] Hawking, Foster & Stein (2008) defines transaction-based systems as ERP systems

advertising campaigns, customer-characteristic segmentation, and cross selling of products;

- Analysing customer lifetime valuation by understanding the pattern of repeat purchases, money spent, and longevity;
- Analysing customer satisfaction through multi-functional processes of on-time delivery, support calls, complaints, and returns;
- Supplying information for procurement decisions such as inventory velocity and supplier delivery performance; and
- Analysing the firm's value-creating activities through analysis of financial statements and financial figures of merit such as profit margins and economic value added.

Under these circumstances, BI can assist in enhancing ERP, achieving customer relationship management (CRM), supporting supply chain management (SCM), and generating near real-time monitoring abilities (Liautaud & Hammond 2001; Payton & Zahay 2005). Moreover, from this perspective, ERP can use information for different functional applications in order to enable costs to be cut, to enhance stronger customer linkages to be created, to innovate near real-time monitoring, and to plan for their businesses (Hannula & Pirttimaki 2003). Most ERP have highly integrated databases used to congregate all needed data modules from the system and load them into a data warehouse or a data mart, and then link to BI tools (e.g. OLAP, DM, query, and reporting). Chung, Lee & Pearn (2005) reported that BI will become a new direction for enterprises with the deployment of ERP, SCM, CRM, etc. It is clear that the use of BI and decision support applications (BIDSA) in the organization is growing at unprecedented levels and shows no signs of slowing down (Chou, Tripuramallu & Chou 2005).

With rapid increases in the number of users considering the value of information, BIDSA has become a critical aspect for organisations in environments of high information usage to consolidate analysis of the data with user friendly reporting capabilities for making intelligent and correct decisions to gain advantage over competitors. It also offers functionality and new ways of doing data analysis and decision-making that no business can afford to ignore. In addition, on the demand and supply side, the use of BI application packages increases worldwide every day. The market for business intelligence solutions has grown quickly (see Figure 2-1). This is being driven by a trend for consolidation, with several large application and software infrastructure vendors initiating major BI acquisitions (Gartner 2008).

From discussion above, it is implied that BI and decision support applications (BIDSA) has now become an essential decision support component for many companies. BI techniques will be embedded into business processes. It is the embodiment of the data-driven DSS. BI as business information and business analyses within the context of key business processes leading to better decisions and actions and that results in improved business performance. Significantly, for business BI in practice is to assist in increasing revenues and/or reducing costs, thereby improving performance and increasing profits. Thus, with the rapid increase in the number of BI software packages and their use by many organisations, these are not only the place where they manage information about products and services, but they also offer commercial value in terms of profitability.

2.4 DEFINITION OF BUSINESS INTELLIGENCE AND DECISION SUPPORT APPLICATIONS

Definitions of "**Business Intelligence and Decision Support Applications" (BIDSA)** are available from a range of different sources but the definitions are still related to each other.

As BI technologies are components of information systems (IS), information technology (IT), and information communication technology (ICT), the terms: "IS, IT, ICT", and "DSS, KMS and EIS" are used in this study and definitions of these terms from the literature are reviewed in this section.

2.4.1 Information System, Information Technology, and Information Communication Technology

IT is viewed as an innovation when it is felt by potential adopters to be relatively new (Rogers 1995) (This is discussed further in section 2.7). According to Huff & Munro (1985), IT refers to a range of technologies, which are involved in information processing and handling, such as computer hardware, software, telecommunications, and office automation, and also includes new systems development methodologies. However, in terms of IT and IS, Maguire, Kazlauskas & Weir (1994) state that *the perspectives from which IT and IS are viewed can lead to some difficulties in reconciling understanding of the terms.*

From the top down *with a broad view*, IT is embedded in the information systems that are the large building blocks of the infrastructure of a society. For example; the education system or the social services systems are examples of information systems (IS). At the *microview*, however, in the management of any particular organisation, whatever its mission, it may be better to work within a definition that, while general, associates IS more closely with the management of organisations. As mentioned before, it is claimed that IS will continue to compose both human informants and humans wanting to be informed. Simultaneously, IT will continue to extend the range and depth of human knowledge that can be stored and made available to inquirers through IS. Turban, Aronson & Liang (2005) claimed that the term IT is used interchangeably with IS. Hence, Turban et al. (2008) showed that the concepts of IS and IT are closely related to each other.

However, according to Senn (2004) during this period of time, IT is defined as a wide variety of items and abilities used in the creation, storage, and dispersal of data and information as well as in the creation of knowledge. That is, information technology includes the IT infrastructure and all other information systems so IT is any hardware or software used to build, operate, or maintain an organisation's information system (IS) applications including decision support tools and technologies as well as the IT infrastructure of transaction processing systems, ERP, servers, networks, and Business to Consumer (B2C) and Business to Business (B2B) websites that enable those applications to function.

Further, IT comprises not only the decision support tools themselves, but also the tools for developing the underlining functional aspects of a decision support system basis (Bhargava, Power & Sun 2007). Forgionne, Gupta & Mora (2002) observed that DSS, EIS, and KMS are currently the area of the information system discipline that is focused on supporting and improving managerial decision-making. Rouibah & Ould-ali (2002) indicated that BI is "decision support capability" considered different than its predecessor, in that it is a strategic tool intended to help with planning and performance measurement, rather than with purely operational decisions (e.g. DSS, EIS).

According to Thomas Jr. (2001) BI is information technology that provides significant business value by improving the effectiveness of managerial decision-making in DSS, EIS, and KMS. These innovations have dramatically reduced the cost of storing, processing, communication and disseminating information (Marakas 1999). As a result, BI is a specific

IT instrument and highly customised IS solution for analysing and updating a large amount of data with potentially useful operational applications in order to enhance decision-making by using more significant information.

According to Knol & Stroeken (2001), IT at a high aggregation level is a new technology paradigm affecting the management and control of production and service systems throughout the economy, based on an inter-connected set of radical innovations in electronic computers, software engineering, control systems, integrated circuits and telecommunications. All terms will merge in time so that they could refer to the deployment of IS/IT (e.g. DSS, EIS, KMS, BI) in business. Thus, it could be implied that most businesses will use various IS/IT components to support and enable a range of business activities.

Buhalis (2003) stated that as it becomes *more difficult to distinguish between each element of the technology*, information communication technologies (ICTs) should be regarded as the entire range of electronics, computing, and telecommunication technologies, hardware, software, and netware which are required for the development and operation of the "info-structure" of an operation. According to Turban et al. (2008), information technology (IT), also known as ICT, is a broad subject concerned with technology and other aspects of managing and processing information, especially in large organisations. IT deals with the use of electronic computers and computer software to convert, store, protect, process, transmit, and retrieve information.

Moreover, as stated by Pant & Ravichandran (2001), IT is computer applications and infrastructure that influence intra and inter firm process and system integration. For example, Bassi (1997); Blundell, Griffith & Reenen (1995); and Wurzburg (1998)   stated that KMS is one type of ICT useful for knowledge management. Therefore, ICTs are an integrated system of networked equipment and software that drives effective data processing and communication for organisational benefits.

Based on these arguments, the concepts of IS/IT/ICT are closely related and may be used interchangeably. BI and decision support technologies are components of IS/IT/ICT; therefore, the terms IS/IT/ICT in this study are similar in concept and related to the use of "BI and decision support applications (BIDSA)".

2.4.2 The Evolution of Decision Support Applications

Using information systems to support decision-making has been very important to business over several decades. Businesses have used a model in analysing business information to tackle complex business decisions. One basic type of information system in decision-making is the decision support system (DSS) technology and applications have evolved significantly.

Holsapple & Whinston (1996) identified five characteristics of DSS as:

- The knowledge that encompasses a component of the decision makers' domain; this includes how to achieve various tasks and possible valid conclusions for various situations
- The ability to acquire and maintain descriptive knowledge
- The flexibility to present knowledge on an ad hoc basis in a variety of customisable formats
- The ability to derive subsets of stored knowledge to facilitate decision-making
- And the flexibility to allow users to choose the sequence of knowledge management activities.

Power (2007) asserted that the five broad characteristics of DSS could be categorised as: communication-driven, data-driven, document driven, knowledge-driven, and model-driven decision support systems. These frameworks are used to help build and understand decision support system technology and application. This is suggested that the technology or application relating to the characteristics of DSS mentioned previously have been used to support decision-making.

However, the demand for IS to support more effective decision-making has increased and DSS once supported individual decision makers, but later DSS technologies were applied to specific groups or teams, especially virtual teams. Thus, systems have evolved to focus on providing tools for ad hoc decision analysis of specific decisions: called “DSS”, and to systems designed to provide updated, often real time, relevant information to senior and middled managers: called “Executive IS”.

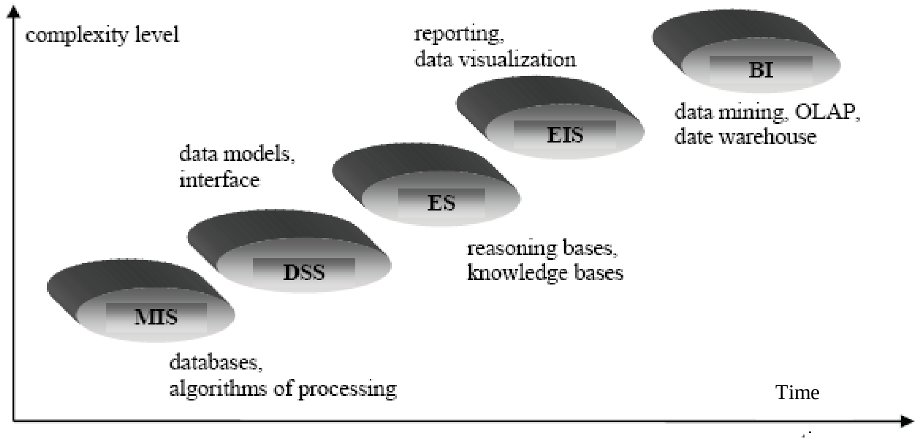
Further, there has been an emergence of systems that target professional and managerial activities by focusing on creating, gathering, organising, and disseminating an organisation’s knowledge as opposed to “information” or “data”. These are referred to as knowledge management systems (KMS). These three systems contribute to individual and organisational improvements in varying degrees and continue to be important components of an organisation’s information technology for assisting decision-making. Thus, DSS, EIS, and KMS could all be recognised as tools/applications for decision support.

Prior to intelligent systems, traditional DSS was designed to empower a small class of applications, normally relating to sales and financial analysis. According to Elam, Huber &

Hurt (1986), traditional DSS have become firmly established in the main stream of IS practice and applications have become common. The real revolution is in the efforts to institutionalise intelligence activities. It is necessary to have a new solution to present business information in a timely and easily consumed way and provide the ability to reason and understand the meaning behind business information through, for instance, discovery, analysis, and ad hoc querying (Azoff & Charlesworth 2004; Lönnqvist & Pirttimäki 2006).

In order to provide in-dept and timely information, BI tools are designed to extend DSS capabilities to support IT applications (e.g. DW, OLAP, DM, SCM, CRM). BI tools apply the DSS functions for viewing the past of today's online operational applications. As a result, the challenge is to be able to utilise the available information, to gain a better understanding of the past, and predict or influence the future through better decision-making by using the advanced decision support tool of BI applications.

According to Anahory & Murray (1997); Berry & Linoff (1997); and Han & Kamber (2001), BI is considered as an important strategic decision support tool for many enterprises. From the Gartner CIO survey, BI remains one of the top priority issues for chief information officers (CIOs) and investment in BI technologies continue to grow (Gartner 2008). Therefore BI is the most strategic information system in many organisations. In order to be able to react quickly to changes that occur in the market, firms need more effective decision support IS that would make it possible to carry out different cause and effect analyses of organisations and their environments. Figure 2-2 shows the development of information systems with decision support characteristics.



Source: Olszak & Ziemba (2004)

Figure 2-2: Development of Information Systems (IS)

2.4.3 Decision Support Systems (DSS)

As concluded by Little (1970, p 470), DSS is defined as "*a model-based set of procedures for processing data and judgement to assist managers in their decision-making*". Power (2002) stated that many academics discuss building DSS in terms of four major components: 1) database management system (DBMS); 2) model base management system (MBMS); 3) user interface subsystem; 4) knowledge-based management subsystem. For easy understanding, Arnott (2004) defines DSS as computer-based information systems that are designed with the specific purpose in order to improve the process and outcome of decision-making.

Decision-making is one of the primary tasks of management and management involves a process of evaluating, selecting, and initiating courses of action (Simon 1977). Human decision-making capabilities have been significantly improved with the use of IT designed specifically to aid business administration in choosing courses of action.

However, as technology advanced, a new generation of managers evolved and the technology helped them make intelligent business decision faster. The way to improved decision-making potential, coupled with increasing IT capabilities, has led to the emergence of business intelligence. By broadening the capability of basic DSS functions, new tools like EIS, KMS, OLAP, data warehouse, or data mining, delivered via web technology, promised managers easier access to tools, models, and data for decision-making (Cohen, Kelly & Medaglia 2001; Power 2002). These more effective decision support tools are combined as BI applications that can help managers to drive decisions, and help to make them more effective (Vitt, Luckevich & Misner 2002).

2.4.4 Executive Information Systems (EIS)

An executive information system (EIS)[9] extends the scope of DSS from personal or small group use to the corporate level. Senior executives can easily access integrated information from a variety of internal and external data sources, to support their analytical, communication, and planning needs (Pervan & Phua 1997). Research by Leidner & Elam (1993) has shown that EIS can increase problem identification speed, decision-making speed, and the extent of analysis in decision-making.

However, in the relatively short period of time BI (e.g. data warehouses) has become the technology of choice for building the data management infrastructure of both DSS and EIS (Parker 1994). McBride (1997) stated that EIS can bring information from the external environment and all parts of an organisation and present it in a way that is meaningful to executive users. Based on this perspective, EIS for users and functions of the system seem to

[9] Watson, Rainer Jr. & Koh (1991) define an EIS as a computerised system that provides executives with easy on-line access to internal and external information relevant to their success factors.

be a reporting function for BI in providing information access (Bergeron & Raymond 1992; Edwards & Peppard 1993; Miller & Mawhinney 1992).

2.4.5 Knowledge Management Systems (KMS)

Knowledge management (KM) is the systemic and organisationally specified process for acquiring, organising, and communicating knowledge of employees so that other employees could make use of it more effectively and productively in their work (Maryam & Dorothy 1999). Knowledge management systems (KMS)[10] provide activities that help in focusing the organisation to acquire, store, and utilise knowledge for such things as problem solving, dynamic learning, strategic planning, and decision-making (Gold, Malhotra & Segars 2001). These include document repositories, expertise databases, discussion lists, and context-specific retrieval systems incorporating filtering technologies.

BI is a broad category of applications and technologies of gathering, accessing, and analysing a large amount of data to make effective business decisions (Williams & Williams 2006). Both KM and BI overlap (Okkonen et al. 2002). Typically, BI technologies include business rule modelling, data warehousing, OLAP, and DM (Loshin 2003). BI deals with and fully utilises vast amount of information in and around the organisation (Buckman 2004; Feng & Chen 2007). Similar to BI, KM is about improving the use of information and knowledge available in organizations (Sun & Chen 2008). BI and KM must be integrated in order to promote organizational learning and effective decision-making, and the effectiveness of BI should be measured based on the knowledge improvement for the organization (Cook & Cook 2000).

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[10] KMS is defined as "IT based systems developed to support and enhance the organisational processes of knowledge creation, storage/retrieval, transfer, and application (Avali & Leidner 2001) and are manifested in a variety of implementations" (Davenport, De Long & Beers 1998)

When BI is used, it generates vast masses of data, which need processing in order to convert data into information and intelligence. An efficient KM will be used for attaching meaning to such information and intelligence. By processing data systematically, data can be interpreted and spread in the form of information and knowledge through both processes. BI concerns itself with decision-making by using data warehousing and OLAP techniques. Data warehousing collects relevant data into a repository where it is organised and validated so it is able to serve decision-making objectives. Similarly, KMS exhibits the ability to help process and organise textual information and data so as to enhance capabilities and to garner meaning and assess relevance to help answer questions, realise new opportunities, and solve problems. Herschel & Jones (2005) note that BI could be used to support knowledge management by providing the analytic processes which transform fragmented organisational and competitive data into goal-oriented "knowledge" and require an integrated database basically provided by a data warehouse. Thus, the use of knowledge management leverages the value of using BI and vice versa.

2.4.6 Business Intelligence and Decision Support Applications (BIDSA)

The term Business Intelligence (BI) has been used in its present sense since a 1964 IBM report and followed by a 1989 Gartner Group article. However, Lönnqvist & Pirttimäki (2006) stated that BI has evolved into a managerial philosophy and a business tool, which can be used to refer to:

"An organised and systematic process by which organisations acquire, analyse, and disseminate information from both internal and external information sources significant for their business activities and for decision-making" (p. 32)

According to Chung, Chen & Nunamaker (2003), BI can be defined as the concepts and methods of acquisition, interpretation, collation, assessment, and exploitation of business-related information. Most researchers agreed that BI is a process which incorporates related technologies (Golfarelli, Rizzi & Cella 2004; Lönnqvist & Pirttimäki 2006; Zanasi 1998). The essence of Lönnqvist & Pirttimäki (2006) definition is confirmed by (Golfarelli, Rizzi & Cella (2004), who stated that BI is the process by which businesses transform relatively meaningless data into useful, actionable information and then into knowledge.

There is a distinction between knowledge and information. Information is patterned data (Liebowitz 2001; Rodrigo, De Mata & Ferreira 2001), while data represents raw, unpunctuated symbols or observations (Davenport & Prusak 1998; Krogh, Roos & Slocum 1994). Knowledge provides the context for creating and understanding information and gleaning information from it sources depending on what is already know (Kogut & Zander 1992; Wiig 1997). For instance, knowledge then incorporates a set of people, principles, facts, and rules of thumb gained by experiences, and which are embedded in human action (Houari & Far 2004).

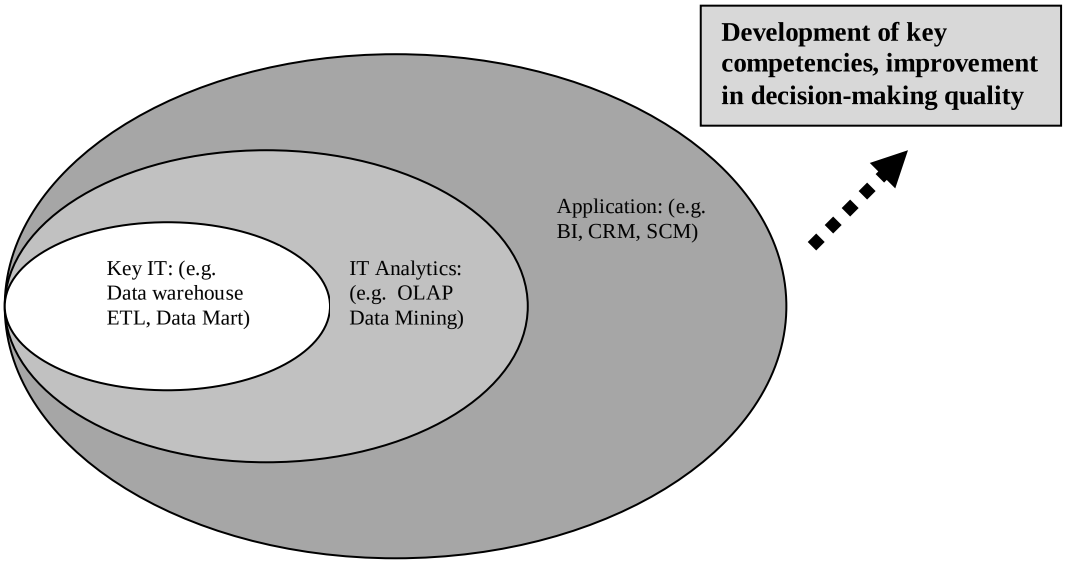
Knowledge in the BI process can be obtained by using a range of different functionality to analyse (e.g. OLAP, DM, data visualisation) (Ou & Peng 2006). Specific knowledge by previous analytics is typically obtained about customer needs, customer decision-making processes, the competition, conditions in the industry, and general economic, technological, and cultural trends. In other words, knowledge obtained by BI is able to identify relationships among data items and enhance their understanding of desired information (Hedgebeth 2007). As a result, knowledge can be used to guide the business in the running of its day-to-day activities, as well as serving as a basis by which strategic planning and decision-making processes can be efficiently and effectively carried out (Golfarelli, Rizzi & Cella 2004; Lönnqvist & Pirttimäki 2006). For example, to apply BI functionality, Lejeune (2001) addressed data mining techniques that allow the transformation of raw data into business knowledge. Emerging BI tools can answer business questions that have been traditionally too-time consuming to solve. With sufficient database size and quality, this can provide business intelligence to generate new opportunities (Lau et al. 2003; Su, Hsu & Tsai 2002).

Unlike the previous systems with decision support characteristics: decision support systems (DSS); knowledge management system (KMS); executive information system (EIS); etc. with limited database, modelling, and user interface functionality, BI systems are data-driven decision support systems (DSS) (Power 2007). Davenport & Harris (2007) pointed that the entire field of systems for assisting in decision support is concluded as BI. BI systems are computer-based information systems that attempt to provide timely and relevant information to management in order to help them make decisions about the operations and the future of their organisations (Olszak & Ziemba 2003).

According to (Houari & Far 2004; Kalakota & Robinson 1999), BI systems comprise a set of tools and techniques that consolidate and transform corporate data into information. The most important components of BI system infrastructure consist of:

- Front-end systems (e.g. OLAP, data mining) that mainly perform versatile analyses of data, and presentation of data.

- Back-end systems (e.g. Extraction-Transformation-Loading (ETL)[11] technique, data warehouse, data mart)) that are related to data integration; both data acquisition and storing.
- Application systems (e.g. BI, SCM, CRM) that support making various decisions on production, sales, competition monitoring, finance) (see Figure 2-3).



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Source: Kalakota & Robinson (1999)

Figure 2-3: BI systems as information technology infrastructure that supports decision-making

Shown as Figure 2-3, this integrated set of applications, technologies, and program products are used to collect, integrate, analyse, and make data available. According to Langseth & Vivarat (2005), data warehousing is considered essential components of proactive business intelligence. Data warehouse is a fundamental function of BI that is able to increase overall data availability, storage capacity, and processing capacity (Negash 2004). Inmon (2005) defines a data warehouse as a collection of data that has the characteristics of subjected,

[11]Erickson (2003) defines ETL as "tools that are pieces of software responsible for the extraction of data from several sources, their cleansing, customization, and insertion into data warehouse".

integrated, time variant and non-volatile. It is meant to be a repository for consolidated and organized data that can be used for analysis (Ericsson 2004). This filled with complete and purified data is a prerequisite for the task of transforming information into knowledge.

Specifically, Golfarelli, Maio & Rizzi (1998); Bouzeghoub & Kedad (2000); and Theodoratos & Sellis (1999) explained that the data warehouse is designed to satisfy the needs of business users and not for day-to-day operational applications. Further, information from the data warehouse is clean and consistent, and is stored in a form business users can understand. Unlike operational systems (general database systems), which contain only current data, the data warehouse can supply both historical and summarised information. Finally, the use of client/server computing provides data warehouse users with improved user interfaces and more powerful decision support tools.

As a data warehouse usually contains aggregated data, it contains two main components: the main integration component, responsible for collecting and maintaining the materialised views which are computed in integrated form from multiple data sources, and the query and analysis component, responsible for filling the information and analysis needs of specific end users (Labio, Quass & Adelberg 1997). Finally, a data warehouse will provide the large-scale data infrastructure that feeds the OLAP data structure which is an in-depth part of data analysis in support of management's decisions (Inmon & Hackathorn 1994). Turban, McLean & Wetherbe (1999) argued hat OLAP and data mining are common methods for retrieving hidden knowledge from the data stored in a data warehouse.

The term "OLAP" by Hart & Porter (2004) was first used in 1993 by Dr. E.F. Codd, the inventor of the relational database. According to Hart & Porter (2004) and Delmater &

Hancock (2001), OLAP is a powerful, highly interactive tool that enables users to, among other things:

- Perform fast and dynamic analysis of aggregate data;
- View information from multiple perspectives or dimensions;
- Carry out trend analysis over sequential time periods;
- Drill-down though various levels of data to retrieve the underlying details.

As above, the primary purpose of OLAP is used to get better understanding of patterns and trends in historical data and to analyse business performance across a variety of metric and functional areas (Chaudhuri & Dayal 1997). They assist in carrying out complex analyses of company performance, customer relations, product profitability, etc. In another words, the effective realisation enables firms to detect weaknesses, treats, and hidden opportunities and chances (Olszak & Ziemba 2003). Friedman et al. (2005) suggested that OLAP can provide significant improvements to established processes that will result in increased revenue or cost saving for an enterprise. The existing literature reveals a large number of OLAP applications. These include marketing and sales analysis, database marketing, budgeting, financial reporting and consolidation, management reporting, profitability analysis, and quality analysis (Hart & Porter 2004; Pendse 2005).

In addition, data mining is known as a powerful tool for knowledge discovery in BI functionality (Chen & Liu 2005). It reveals meaningful information/patterns and trends about business from the data warehouse that queries and reports do not reveal effectively, using various techniques (Gray 1996). Many techniques (e.g. artificial intelligence, statistical analysis, multidimensional data analysis, and geographical information systems) are used for discovering new information, patterns, and trends from a company's databases or enterprise data warehouse. Appropriate data mining tools, which are good at extracting and identifying useful information and knowledge from customer databases, are one of the best supporting tools for making different CRM decisions (Berson, Amith & Thearling 2000). Much literature showed that with comprehensive customer data, this technology can provide business intelligence to generate opportunities (Ngai, Xiu & Chau 2009; Su, Hsu & Tsai 2002; Zhang et al. 1999).

In term of BI applications research by Holsapple & Sena (2003), BI can be applied to many areas that are related to enterprise management process, some of which have formed their own systems with specific characteristics. Much of the application scope involves the BI system in the areas of CRM, SCM, or human resource management (HRM). For example, the analytically enabled technologies usually engage with different analytical information applications: the customer relationship management analytic (CRM) which provides multidimensional data in the form of key performance indicators (KPI) to support the decisions in terms of marketing, sales, services, and interaction, and the supply chain management analytic which optimises data for automation of decision process in terms of planning, pricing, scheduling, and product shipping (Hawking, Foster & Stein 2008). Finally, the application supporting near real time monitoring represents the process to monitor business events and provides output in order to make decisions at near real-time (Azvine, Cui & Nauck 2005).

Many vendors also have BI tools to access their data modules directly. The most important technique is to congregate all desired data from the ERP, CRM, SCM systems and then load this into a data warehouse or a data mart, and link to BI tools (Chou, Tripuramallu & Chou

2005). These modules add value to enterprise systems. Enterprise-wide transaction data can be collected and then analysed for decision-making usage.

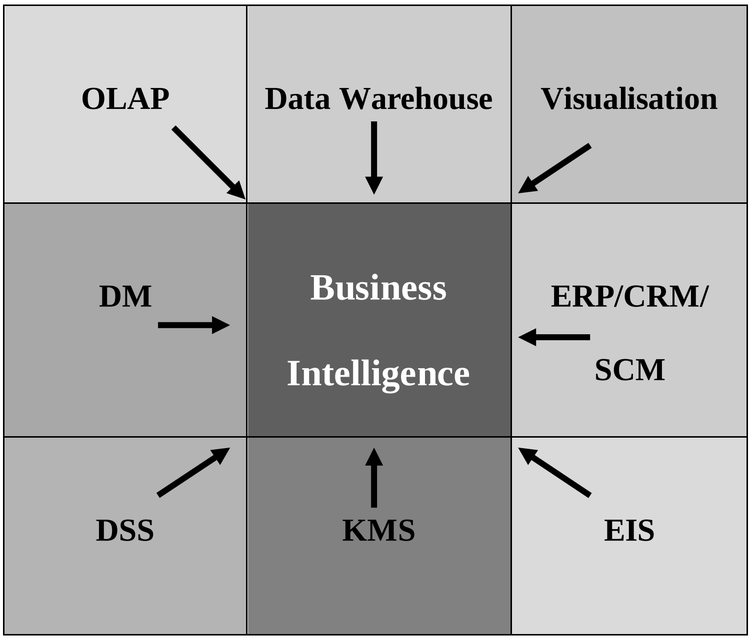
As discussed above, it is implied that BI represents the step beyond data warehousing. It has become an object in transforming a bundle of naïve techniques into a well founded approach to information extraction and processing (Golfarelli, Rizzi & Cella 2004). BI tools are also used to align the path of related IT innovation. Thus, all decision support applications mentioned above are related and overlapped. According to Arnott et al. (2004), personal or group decision support systems (PDSS or GDSS), enterprise information systems (EIS), online analytical processing systems (OLAPS), data warehousing (DW), and business intelligence (BI) can be considered as one in a DSS in terms of contemporary professional practice. Arnott & Pervan (2005) declared the evolution of DSS using seven sub-groupings of research and practice: personal DSS, group DSS, negotiation support systems, intelligent DSS, knowledge management-based DSS, EIS, data warehousing, and BI tools. They found that the sub-groupings overlap, but reflect the diverse evolution of prior research in term of the characteristics of decision support applications as mentioned before.

It could be concluded that BI assists in strategic and operational decision making. A Gartner survey ranked the strategic use of BI as follows (Willen 2002).

- Corporate performance management (e.g. Modelling and Optimisation, Consolidation, Balance Scorecard, Budget Plan/Forecast, Strategy Reporting, Ad Hoc Query and Reporting)
- Optimising customer relations, monitoring business activity, and traditional decision support
- Packaged standalone BI applications for specific operations or strategies

- Management reporting of BI

From time to time, BI is a natural effect of a series of previous systems designed to support decision-making. BI can apply to many systems or functions (e.g. DSS, EIS, KMS, DW, OLAP, DM) and pull information from many other systems or applications (e.g. ERP, CRM, SCM). Figure 2-4 depicts some of IS applications that are linked by BI.



Source: Negash (2004)

Figure 2-4: BI in relation of information systems for enhancing decision-making

Compared with traditional DSS, EIS, and KMS, the main difference is that the users of BI are not limited to enterprise leaders and decision makers, but are extended to all people throughout the organisation, including users within enterprises; general managers, department staff, and users out-of-enterprises; customers, suppliers, and partners (Arnott & Pervan 2008).

In addition, the capabilities of decision support applications that are based on a traditional database and knowledge base are limited through lacking enough information (Eom 1999).

Thus, the process of BI has more powerful ability of data integration, data analysis, knowledge discovery, and better decision-making to achieve competitive advantage (Frates & Sharp 2005). Research from "The 2003 CIO Insight Business Intelligence Research Study" from more than 570 IT executives insisted that: 1) some 88 % of companies have confidence in the accuracy of the customer information they gather; 2) the technologies used to collect, aggregate, analyse, and report along with the percentage response in parentheses are: reporting tools (82.1), automated data/information feeds (79), intranets/portals (70.4), or data warehousing (69.8), data visualisation (41.4); and 3) BI seem to be necessary (Frates & Sharp 2005).

Based on the above, it can be seen that the term "business intelligence" is closely related in a similar context to decision support applications: "DSS", "EIS", "KMS", etc. Therefore, the meaning of adoption of BI and decision support applications (BIDSA) by an ERP perspective in this study based upon these observations, is defined from the decision support application perspective as the provision of information analysis between ERP user organizations and BI applications, including provision of ERP user information, transaction information, BI application information, and decision-making characteristic information.

Therefore, the definition of BIDSA can be defined as follows:

- **Adoption of "business intelligence and decision support applications (BIDSA)" by an ERP perspective** involves the use of decision support applications and BI functionality for making an effective and efficient decision with accurate information. This may include the use of core database technology to manage data; the use of enabling technology for data analysis in analysing data; the use of a particular application solution with real-time reporting and monitoring functions for proving feedback and updating, pulling, analysing, and retrieving data.

2.5 THE KEY TO SUCCESSFUL INFORMATION SYSTEMS FOR DECISION-MAKING

The development of information system tools has made it easier and cheaper to store, reuse, and share valuable information rather than to have to reinvent it as needed (Greengard 1998; Sena & Shani 1999). For example, studies addressing the effects of IS use on decision-making processes include Dean & Sharfman (1996), Kendall (1999), and Rai & Bajwa (1997). Research in this area has typically focused on how IT can improve the efficiency with which a user makes a decision, and can improve the effectiveness of that decision (Pearson & Shim 1995). Rumizen (1998) pointed out that more organisations have begun to take advantage of new information systems or telecommunication technologies to develop a technical infrastructure to facilitate information/knowledge for efficient decision-making.

The importance of IS/IT/ICT in designing decision support applications has been highlighted by a number of researchers. For example, the work of Inmon (2005) and Kimball (1996) promoted a data warehouse as a solution for integrating data from diverse operational databases to support management decision-making. Shim et al. (2002) pointed out that a data warehouse is the foundation of advanced decision support applications. Burstein, Bui & Arnott (2001) suggested that based on DSS research and practice, data warehousing is one of the best technologies of the intelligent or knowledge-driven DSS in the new millennium. Kimball (1996), Wang (1998), and Watson & Haley (1997) pointed out that to create data quality is one of the key factors that are important to data warehousing technology in providing high-quality data to decision makers. More specifically, data accuracy, completeness, and consistency are critical aspects of data quality in a data warehouse (Lyon 1998; Shanks & Darke 1998).

However, Sakaguchi & Frolick (1997) suggested that scalability, standardisation, and security are also important features in the useful data warehouse but the success of the system is more than likely to be judged by how easy and efficient it is for both end users and IS professionals to generate information to support decision-making (Shin 2003; Vatanasombut & Gray 1999; Watson & Haley 1997). Conversely, a data warehouse that is not user-friendly in either its user interface or the analysis tools provided can result in millions of dollars of unused software and unrealised return on investment (Gorla 2003; Johnson 2004). Thus, to create useful IS in decision support applications, the system should be ease to use, produce more and better quality information, and be interactive and efficient.

In the system quality literature, Delone & McLean (1992) have identified four factors that affect performance of system quality: system flexibility, integration, response time, and reliability. Flexibility and integration are particularly important for decision-support applications (Vandenbosch & Huff 1997). Systems that integrate data from diverse sources can improve organisational decision-making (Wetherbe 1991; Wyboa & Goodhue 1995), and flexibility allows decision makers to easily modify applications as their information needs change (Vandenbosch & Huff 1997). Thus, this decision support application can provide the infrastructure that integrates data from multiple sources and flexibly support current and future users and applications (Gray & Watson 1998; Sakaguchi & Frolick 1997).

Wixom & Watson (2001) have showed that data quality is of critical importance as another component of system quality in a data warehouse. As described by Watson & Haley (1997), more and better information is one of the purported benefits of data warehousing. Sakaguchi & Frolick (1997) discussed the data warehouse with its ability to provide quantitative values, or metrics that allow a firm to benchmark performance in an effort to measure progress. The quality or usefulness of information is also used by both Shin (2003) and Wixom & Watson (2001) as one of the key successful factors. Thus, to create efficiency of a decision support application, the system should provide data-driven quality to users or decision makers.

Holsapple & Whinston (1996) and Dhar & Stein (1997) have suggested that intelligent or knowledge-driven DSS could create information that is relevant for decision-making. It is necessary for business organisations to gain information/knowledge by developing contemporary decision support applications to increase their ability in making decisions (Sakaguchi & Frolick 1997). In another way, a decision support application provides information/knowledge for employees to make decisions to do their jobs more effectively (Poe, Klauer & Brobst 1998).

In summary, then, based on the above information, the basic elements of successful decision support applications that can meet decision makers or users' needs should include both technical system characteristics (database; analysis tools) and business functions in terms of quality and quantity of information (knowledge; intelligence), easily innovative use, and security and access authorisation.

2.6 DECISION SUPPORT INFORMATION SYSTEMS EVALUATION

Dispersion of information assets and their frequently tacit nature result in some insufficiency of up-to-date models of information management used for decision-making (Bui 2000; Power 2001). Having IS for decision support provides an enterprise with important business opportunities and a competitive edge. However, as more and more decision support applications proliferate and are important, the purposes of analysing problems in predicting patterns and trends are more intensifying and in-depth. It is suggested that enterprises are no closer to embedding analytics in the next wave of business intelligence (Foster, Hawking & Stein 2005). How strategically to bring BI closer to the operations and processes that drive business on a daily basis is still the basic difficulty in current businesses (Wang & Wang 2008).

Yet, it is extremely challenging to determine how to retain currently usable information and generate actionable information or knowledge in order to enhance competitiveness. BI as a solution would be major technologies that support a heterogenic decision-making environment. This technology has become crucial in an environment where increasing competition, sophisticated and informed consumers, unpredictable market fluctuations, and changing regulatory environments are putting much pressure on business organisations (Hedgebeth 2007). Hart & Henriques (2006) and Lönnqvist & Pirttimäki (2006) have suggested that decision-making professionals should evaluate the content and tools of their decision support applications to create knowledge serving as a basis of strategic planning and decision-making.

Therefore, increasing levels of change in competition and technology in the business environment are causing organisations to dramatically modify their strategies, information architectures, and methods of IS for conducting business (Katarina & Bach 2007). The solution is BI, which provides a set of technologies and IS products for supplying users with the information they need to answer business questions, and make tactical and strategic business decisions.

2.6.1 The Essence of Information Systems for Decision Support Characteristics

The rapid development of IT has resulted in various IS tools that enterprises can adopt to enhance their transaction-based systems with knowledge processing capability to support more strategic and complex decisions. The data warehouse has surfaced as a key source of information for knowledge workers and managers. Its well-publicised value in offering high query-response performance and increased information accessibility, as well as being an integrated source of data, is creating an extremely popular environment for decision support in firms (Watson et al. 2004; Watson & Haley 1997).

Many firms have turned to data warehouse to assist in making decisions about changes needed (Little Jr. 1998). Data warehouse has been cited in the literature as being one of the most powerful strategic weapons (Park 1999). Data warehouse emerged in response to the problem encountered in providing information for use by DSS, with the main limitation being the lack of separation of operational data suitable for decision support (McFadden 1996)

Unlike numerous operational systems, these are not designed to support strategic decision-making. Operational systems are designed to support and maximise the day-to-day, value creating work (Connolly & Begg 2002; Connolly & Begg 2005). There are several reasons why existing operational systems could not meet these needs. Singh (1998, p.16) mentioned the following: 1) the lack on-line historical data; 2) the data required for analysis resides in different operational systems; 3) the query performance is extremely poor which in turn impacts performance of operational systems; 4) the operational database designs are inadequate for decision support.

Operational systems are optimised to automate business operations and must be efficient with transactions that are predictable, repetitive, and update intensive. These systems are organised around business functions and the processes building up these functions (Barquin & Edelstein 1997). Conversely, data warehouse systems are designed to support efficient processing and presentation for analytical and decision-making purposes and to provide the decision makers with suitable data and information (Poe, Klauer & Brobst 1998). A data warehouse holds data that is current, historical, detailed, and summarised to various levels. Apart from being supplemented with new data, the data in a data warehouse is seldom subject to change (Connolly & Begg 2002). The number of users served by a data warehouse is smaller than for operational systems (Barquin & Edelstein 1997).

On the other hand, the data warehouse is designed to support relatively low numbers of unpredictable transactions that require answers to queries that are unstructured, heuristics, and ad hoc. The data in a data warehouse is organised according to the requirements of potential queries and supports strategic decisions of managerial users (Connolly & Begg 2002). Moreover, the time horizon for holding the data in a data warehouse is importantly extended compared to operational systems. Generally, the time horizon for a data warehouse is five to ten years, whereas an operational system holds its data 60 to 90 days (Inmon 2005). The following table shows the comparison of operational information systems and data warehouse (see Table 2-1).

Operational Systems	**Data Warehouse Systems**
Application-oriented	Subject-oriented
Transaction-driven	Analysis-driven
Hold current data	Hold current and historical data
Store detail data	Store summarised and detailed data
Repetitive processing	Ad hoc, unstructured, and heuristic processing
Predictable pattern for usage	Unpredictable pattern usage
Support day-to-day decisions	Support strategic decisions
Serve large number of operational users	Serve low number of managerial users
Data is dynamic	Data is static

Source: Connolly & Begg (2002)

Table 2-1: Comparing operational systems (OLTP: on-line transaction processing) and data warehouse systems

However, in today's competitive age, as data is becoming an increasingly significant resource in supporting organisational procedures, the quality of the data that executives use becomes critical (Paradice & Fuerst 1991). Steiger (1998) suggested that the data warehouse has presented decision-makers with far more information, in a far more flexible form than has been true in the past. Accordingly, data warehouse applications have become an essential component of BI and decision support applications.

For example, previous study indicated that the introduction of data warehousing[12] technology and OLAP techniques has greatly improved traditional EIS (Chen 1995) and has led to a new EIS architecture that is sometimes referred to as contemporary EIS architecture (Fernandez & Schnedier 1996). In this architecture, the centralised database is replaced by a data

[12] Data warehousing is defined as a relational database specifically organised to provide data for easy access (Turban, Aronson & Liang 2005).

warehouse, and OLAP techniques are adopted for multidimensional data analysis and information presentation (Hammer et al. 1995).

As data warehouses provide the data infrastructure for management support systems, that include many decision support applications: DSS, EIS, OLAP, SCM, CRM, BI etc., data warehousing supports these applications by providing a collection of tools which: 1) collect data from a set of distributed heterogeneous source; 2) clean and integrate this data into a uniform representation; 3) aggregate and organise this data into multidimensional structures which are suitable for decision-making; 4) refresh it periodically to maintain the data up to date and accurate.

There are many benefits that a data warehouse can provide. For example, the data warehouse can improve performance in better-targeted products, improved customer relation management, and produce greater operational efficiency (Cooper et al. 2000; Moore & Wells 1999). Srivastava & Chen (1999) pointed out that it also results in reengineering of business processes. For instance, automated and integrated information delivered from the data warehouse may substantially free up managers' time and efforts, thereby increasing their availability for other tasks.

The importance of data warehouse in supporting and improving decision-making is recognised as major (Ghoshal & Kim 1986; Martinsons 1994; Rouibah & Ould-ali 2002), but the data warehouse does not provide adequate support for knowledge intensive queries in an organisation. The emerging heterogeneity of the decision environment is stimulating the need to explore more effective techniques for mining and presenting data in a meaningful format

(Rundensteiner, Koeller & Zhang 2000). Thus, the data warehouse can support multiple beneficial applications rather than being an independent application.

Specific techniques such as OLAP (Datta & Thomas 1999) and data mining (Drew et al. 2001) to produce information can improve performance. OLAP is an enabling technology that allows manipulation of enterprise aggregate data across many dimensions such as product, time, and location, etc. (Codd, Codd & Salley 1993). For example, by using OLAP and data mining tools, firms are able to exploit insights gained from their data warehouse to significantly increase sales (Cooper et al. 2000; Heun 2000; Whiting 1999), reduce costs (Watson & Wixom 1998), and offer new and better products or services (Cooper et al. 2000; Watson & Wixom 1998). Moreover, these techniques enable an organisation to detect weaknesses (e.g., customer dissatisfaction) as well as hidden opportunities (e.g. customer segmentation). Organisations can use these applications to simply provide resources to end-users or to guide end users in making a better decision (Silver 1990).

According to the combination of core technologies, enabling technologies, and BI application solutions, (Brackett 2001) and (Hill & Scott 2004) stated that these decision support applications aim at the development of an accurate understanding of business dynamics. They also enable the organisation to monitor its environment and observe business trends, to detect new opportunities and avoid threats, by analysing the complex business environment in order to make decisions (Lönnqvist & Pirttimäki 2006). These processes are consistent with the most important components of the BI infrastructure of (Kalakota & Robinson 1999), which consists of 1) key IT (e.g. data warehouse); 2) IT potential (e.g. OLAP, data mining); and 3) decision support applications (e.g. BI, CRM, SCM).

An important role of decision support applications is to provide information for users to analyse situations and make decisions. Organisations that are interested to improve the quality of decision-making, image, or quality of partner service should incline towards the development of information technology infrastructure that will represent a holistic approach to business operations, customers, suppliers, etc. (Wells & Hess 2004).

Theory and practice show that the above-mentioned requirements are largely met by “Business Intelligence” (BI) systems (Liautaud & Hammond 2001; Olszak & Ziemba 2004; Turban & Aronson 1998). Huber (1990) and Leidner & Elam (1995) proposed that the use of computer assisted information storage and acquisition technologies leads to organisational intelligence that is more accurate, comprehensive, timely and available. Olszak & Ziemba (2006) have concluded that the success of many decision support applications affects decision support.

In summary, then, based on the above information, the infrastructure of a successful decision support application that can meet decision makers’ needs should include core technologies, enabling technologies, and application solutions in terms of quality of information, system reliability, ease of use, and speed (Gray 1993; Liautaud & Hammond 2001; Olszak & Ziemba 2004). Thus, organisations and their decision support applications must embrace procedures that can deal with complexity and go beyond the technical orientation of previous decision support characteristics.

2.6.2 The Important Elements of Successful IS for Decision-Making

Many prior studies have identified the various variables that affect the success of decision support applications. For instance, a widely used approach for investigating the factors related to the successful implementation of computer-based systems has been to group these factors into four categories: 1) the implementation process; 2) the business tasks involved; 3) the decision makers; and 4) the nature of the DSS (Fuerst & Cheney 1982; Igbaria, Parasuraman & Pavri 1990; Lucas 1978; Sanders & Courtney 1985).

However, Guimaraes, Igbaria & Lu (1992) applied this classification and extended it into 6 sets of variables: 1) characteristics of the implementation process (top management support, user training, and user involvement); 2) characteristics of the business task (task structure and certainty, task difficulty, task variability, and task independence); 3) characteristics of decision makers (organisational level and DSS experience); 4) characteristics of DSS (the supported phase, level of managerial activity and source of information); 5) user satisfaction with the DSS; and 6) user perceptions of DSS benefits. The findings indicate that DSS success, as measured by DSS satisfaction and perceived benefits, depends on several factors: previous user experience with DSS, user involvement, user training, top management support, information sources, the level of managerial activity, and task structure, difficulty and interdependence.

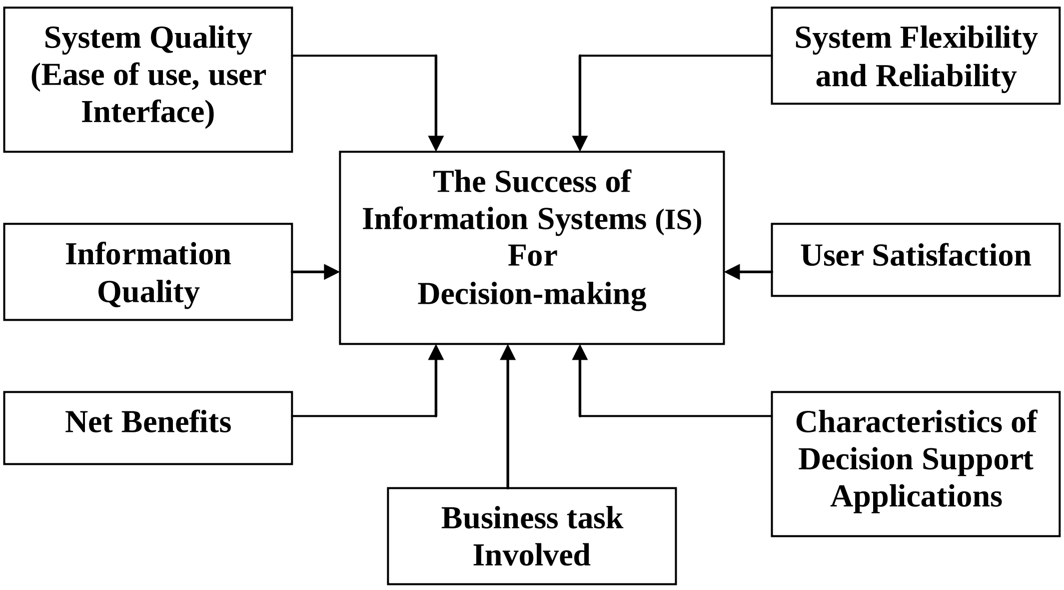
Furthermore, the IS success model by Delone & McLean (1992) and Delone & McLean (2003) provided an overall conceptual framework for identifying the dimensions studied and corresponding features. Drawing on the work of Seddon (1997), three dimensions of IS success were: data quality, system quality, and perceived net benefits. Previous studies focusing on decision support applications in organisations have identified the important elements of decision support applications (e.g. BI systems). For example, Shin (2003) adopted Delone & McLean’s (2003) model and Seddon’s (1997) model for identifying influencing factors of data warehouse success and grouped into six categories: 1) system quality; 2) information quality; 3) service quality; 4) use; 5) user satisfaction; and 6) net benefits. The findings indicate that user satisfaction was affected by such system quality factors as data quality, data locatability, and system throughput.

Then, Srivihok (1999) found that team communication skill and user attitude are the most important factors for decision support application (EIS) success. Yoon, Guimares & Oneal (1995) reported that the quality of developers for the system, end-user characteristics, degree of user involvement, and shell characteristics (e.g. flexibility of knowledge representation and inference engine, user interface, easy to use, etc.) significantly influenced the decision support application (expert system).

Next, Wixom & Watson (2001) examined the factors that affect data warehousing success. The finding indicates that data quality and system quality had significant relationships with perceived net benefits. These results show that a data warehouse with good data quality and system quality improves the way data is provided to decision support applications and decision makers. Rudra & Yeo (1999) added completeness of data, contingency of data entry, and accuracy of data as good data quality.

Bharatia & Chaudhury (2004) used the IS success model of Delone & McLean (1992) to investigate decision-making satisfaction of web-based DSS. As decision-making satisfaction scrutinises the ability of a system to support decision-making and problem-solving activities, this model indicates that use and user satisfaction are direct antecedents of individual and organisational impacts. They found that information and system quality influence decision-making satisfaction. They suggested that ease of use, convenience of access, and system reliability also influence the decision-making satisfaction of users.

From these prior studies, several attributes were identified as important in the process of creating and implementing successfully advanced decision support applications (BI systems) and may potentially make managers and knowledge workers take advantage of the system to perform complex tasks, to support decision-making, and to seek information critical for enhanced productivity. Figure 2-5 below summaries the important factors in the success of a decision support characteristic.



Sources: Fuerst & Cheney (1982); Sanders & Courtne (1985); Fuerst & Cheney (1982); Sanders & Courtney (1985); Lucas (1978); Igbaria, Parasuraman & Pavri (1990); Guimaraes, Igbaria & Lu (1992); Yoon, Guimares & Oneal (1995); Wixom & Watson (2001); Bharatia & Chaudhury (2004)

Figure 2-5: Important factors in the success of information systems from literature

2.6.3 The Performance of IS in Decision Support Characteristics

Firms are facing stiff competition and increased uncertainties. As a result of uncertain information, decision makers must accept the "bounded rationality" (March & Simon 1958) that they should reduce their uncertainty by obtaining as much reliable and consistent information as possible. Information systems have recognised decision support applications as powerful business tools for personnel use and for organisations to gain competitive advantage (Leitheiser & Wetherbe 1986).

Previous studies on decision support applications have shown that the use of decision support technology in business organisations focuses on user overall satisfaction and decision-making satisfaction (Cats-Baril & Huber 1987; Mahmood & Sniezek 1989). Improved decision quality and performance to create profitability are perceived benefits of decision support applications (Aldag & Power 1986; King & Rodriguez 1978; Kottemann & Remus 1989). Among these, user satisfaction and perceived benefits are widely regarded as the prime criteria of decision support applications.

Several studies have shown that information and system quality are important to make a quality decision and decision makers must have quality information pertinent to the decision at hand (Guimaraes & Igbaria 1997; Lucas 1981). Thus, improving system quality should lead to enhanced decision quality. Then, due to the benefits of data warehouse for creating a competitive advantage, many firms have launched data warehouse for better quality of decision support applications.

Research on data warehouse has been mainly descriptive or conceptual (Sakaguchi & Frolick 1997; Schardt 1997; Weilbach & Viktor 1999). Only a few studies (Speier, Palmer &

Bergman 1998; Wixom & Watson 2001) were empirical. Haley (1997) viewed the data warehouse as an IT infrastructure that provides appropriate data and tools to support decision makers and contended that data warehouse provided a unique opportunity to improve the IT infrastructure.

For example, Watson & Haley (1997) found that data warehouse was used throughout the organisation and also supported EIS. According to Park (2006), decision support users can improve decision performance by implementing a data warehouse. The findings provide empirical evidence to support the basic concepts of the IS success model that assumes positive impacts of system quality and/or information quality on decision performance through system use. Rudra & Yeo (1999) also reported that their research showed 86% of the respondents feel that data warehouse would bring about improved customer service, and reduced risks. 99% agreed that ultimately, the data warehouse would help improve strategic decision-making. However, as most data warehouses were customer-oriented, another benefit was the increased opportunity between the organisation and the customer (71%).

This capability of EIS can support executives to arrive at a decision easily, and with accuracy, in many ways. Much previous research declared a variety of benefits of EIS to users: 1) data in meaningful formats; 2) time saving; 3) Improved efficiency and communication; and 4) increased business benefits (Nord & Nord 1995; Rainer & Watson 1995; Rockart & De Long 1988; Salmeron, Luna & Martinez 2001). Leidner & Elam (1993) and Leidner & Elam (1994) examine the effects of EIS use on aspects of the decision-making process by 46 executives. The results show increasing problem identification speed, decision-making speed, and the extent of analysis in decision-making.

Brohman et al. (2000) reported that the influence of new insight on decision-making performance was consistently found in this study. The results suggested that the more queries generated to explore data, the more insight the analyst would generate about the task at hand. This identifies the effectiveness of knowledge sharing and networking with other analysts and managers to; 1) clarify data analysis requirements, and 2) gain further insight into the data and its relationships. Key data-driven decisions were described as both strategic and operational. Strategic decisions related mostly to site location, product category management, promotional vehicles, and store merchandising. Operational decisions were more specific to business operations and concentrated on up-sell/cross-sell campaigns and targeted promotions. Thus, BI would generate new ideas that enabled more informed decision.

2.6.4 Decision Support Characteristics in ERP Systems

2.6.4.1 The Importance of ERP

It is implied that almost all larger organisations have already implemented and completed ERP however the ERP market is still showing progressive growth (Pamatatau 2002). More than 50% of the large enterprises in the U.S., Europe, and the Asia Pacific region including Australia already have ERP systems in place, and more medium-sized enterprises are embarking on ERP system implementation (Forrester Research 2005). With over 60 percent of the Fortune 1000 companies penetrated, major ERP vendors are increasing targeting small- and medium-sized enterprises (SMEs) to generate new customers (Bingi, Sharma & Godla 1999; Piturro 1999).

ERP systems have traditionally been used by many industries such as manufacturing, retailing, aerospace, and government sectors while they have recently been implemented in the finance, education, insurance, retail, and telecommunications industries (Chung & Snyder 2000). A report from Stedman (1999) by Computer Economics Inc. stated that 76 percent of manufacturers, 35 percent of insurance and healthcare companies, and 24 percent of government sectors already have an ERP system or are in the process of installation. These systems currently become important infrastructure for many organisations. Suggested by Chen (2001), organisations chose and deploy ERP systems for a variety of benefits and strategic reasons. Many researchers believe the growth in the uptake of ERP systems is due to several business needs to:

- Streamline and improve business processes
- Better manage IS expenditure
- Meet competitive pressures to reduce costs
- Increase responsiveness to customers and their needs
- Integrate business processes
- Provide a common platform and better data visibility, and
- Use a strategic tool in moving toward electronic business (Davenport, Harris & Cantrell 2003 ; Markus, Petrie & Axline 2001; Somer & Nelson 2001).

Thus, many expect that the most important development in the corporate use of IT has been the usage of ERP systems (Davenport 1998). Hedman & Borell (2002) indicated that ERP systems are in most cases implemented with the goal to improve strategic, organisational, business, management, operational, IT-infrastructure, or decision-making aspects of the organisation. Many studies have concluded that ERP systems can bring benefits in operational efficiency, reduce costs to organisations and enforce a discipline of best practice and consistency (Edwards, Peters & Sharman 2001; Marbert, Soni & Venkataramanan 2001; Van Everdingen, Van Hillegersberg & Waarts 2000). For example, Escalle, Cotteleer &

Austin (1999) suggested that potential benefits include drastic declines in inventory, breakthrough reductions in working capital, abundant information about customer needs and wants, along with the ability to view and manage the extended enterprise of suppliers, alliances, and customers as an integrated whole.

Moreover, based on previous research, ERP serves numerous functional areas in an integrated fashion, attempting to automate operations from the application of BIDSA, SCM, CRM, financial and cost accounting, human resources, and almost any other data oriented management process (Newell et al. 2003; Ng & Ip 2003; Ragowsky & Somers 2002). Thus, it is implied that ERP is now considered the standard system upon which many enterprises are operating their business (Lengnick-Hall, Lengnick-Hall & Abdinnour-Helm 2004).

Despite the support current ERP systems provide for process coordination and data integration, most of them – especially legacy ones – lack advanced decision support capabilities, resulting therefore in decreased company competitiveness. Davenport (2000) suggested that decision-making capabilities should act as an extension of the human ability to process knowledge management systems with the classical transaction-based systems, while Carlson and Turban (2002) claimed that the integration of smart add-on modules to the already established ERP systems could make standard software more effective and productive for the end-users.

Regarding decision support capabilities, Davenport, Harris & Cantrell (2004) suggested that ERP can enable BIDSA through integrating, optimising, and informing that can affect data integration, standardisation of strategic processes, and providing context-rich information to support decision-making respectively. However, the usefulness of BI relies largely on the data infrastructure (Gartner 2003). ETL and data warehouse (e.g. SAP[13]'s data warehouse) have an important role in business intelligence (McDonald et al. 2002; META Group 2004). Holsapple & Whinston (1996) reported that one key characteristics of any decision support system including a data warehouse is to encompass a component of the decision maker's domain, and to achieve various tasks and possible valid conclusions for various situations.

For example, SAP data warehouse technology is known as "Business Information Warehouse" (BW). Stein & Hawking (2002) performed analysis of SAP's Australian customers and identified BW (data warehouse) as the most common solution implemented post core ERP. The META group's research found that 56% of SAP customers who had implemented three or more modules planned to implement BW in the next two years. This group increased to 63 percent when customers have implemented five or more modules (Schlegel 2004).

However, SAP can accomplish more strategic solutions that rely on BW in a specific business domain to assist decision-making. For example, CRM analytics support the decisions associated with customers in terms of marketing, sales, and service. These use information captured and applied to a pre-stored scenario, and much of the required information is supplied via the BW solution (McDonald et al. 2002). BW plays a role as the extractor, integrator, and repository for this data.

Thus, the development of ERP has resulted in the development of a broad range of "bolt-on" solutions. Accordingly, the solution built upon the underlining data contained within ERP and providing extended functionality to assist with more strategic decision-making is

[13] System Application Product (SAP) is defined as a "business software as comprising enterprise resource planning and related applications such as supply chain management, customer relationship management, product life-cycle management, and supplier relationship management" (SAP 2008).

"business intelligence". Concluded by Luftman, Kempaiah & Nash (2006), business intelligence is one of the top five applications and technology developments as key issues for IT executives in many firms. It is implied that business intelligence (BI), is a currently effective decision support application in terms of being an add-on application in creating "intelligence" of information, and system capability plays a crucial role in strategic decisions for an ERP user organisation. For example, Galialis & Tatsiopoulos (2004) utilised advanced IT systems to effectively support the planning and management of distribution operations, and particularly, the transportation processes. The combination of an SCM application with a geographical information system[14] (GIS) integrated with an ERP software resulted in their decision support tool. These are now acronyms which are familiar to most of the people interested in ERP.

As discussed above, it is clear that the role of IT, especially BIDSA, has increased in importance to many businesses including firms implementing ERP. However, for many companies today, the question is not whether ERP is needed but rather what kind of system is needed? IT/IS/ICT including BIDSA are considered as an important strategic decision support tool to adopt for many enterprises. Thus, an ERP perspective will be a suitable candidate for the study the adoption of "**BIDSA"** in business organisations.

2.6.4.2 Decision Support Performance of ERP

Many studies of ERP have shown issues about ERP development and implementation (Davenport 1998; Holland & Light 1999; Koh, Soh & Markus 2000). For example, Davenport (1998) showed that management and implementation of ERP systems have tended

[14] Turban, Aronson & Liang (2005) define GIS as a tool of business intelligence (BI) that use spatial data, such as digitised maps. A combination of text, graphics, icons, and symbols on maps.

to provide integrated transaction processing and access to information that spans multiple organisational units and multiple business function aspects (Davenport 2000), rather than on their decision-support processing.

In 1998, Deloitte Consulting, in association with Benchmarking Partners, Inc. conducted a survey with Fortune 500 firms in manufacturing and consumer industries that they labelled as "ERP's Second Wave" (Deloitte Consulting 1999). The survey found various technological and operational motivations for implementing ERP. Seventy % of respondents expected that their ERP would provide them with improved quality and visibility of information, ultimately leading them to better decision-making. However, 16% of the respondents realised that ERP actually improved the quality and visibility of their information.

Davenport (1998) suggested that the need to make sound and timely business decision is a major concern for ERP. One such comment came from Adam (2001):

> *… But ERP packages are not sufficient from a decision-making point of view. They constitute cast repositories of data that provide a perfect basis for decision-making, but based on empirical research carried out recently, it seems that the reporting capabilities of many ERP packages available is not sufficient for organisations that implement them. Despite vendors' claims that their software includes leading-edge reporting capabilities, many organisations find themselves purchasing additional software to fully exploit the large volumes of data contained in their newly-acquired systems. In one case we studied, managers initially tried to make use of the functionality provided by their package, but became disillusioned with the lack of flexibility of the reporting tools and the excessive time needed for staff to become fluent in developing additional reports or amending existing ones.*

ERP systems, because of their transaction-centric characteristic, have inadequate capability to support decision-making in organisations (Davenport 1998). Even though increased transaction processing efficiencies, higher quality information and greater accessibility of information, and better support for ad hoc reporting are some benefits of these implementation (Fahy & Lynch 1999; Granlund & Malmi 2002; Scapens & Jazayeri 2003). A study by Booth, Matolcsy & Wieder (2000) in Australia indicated that ERP performs better in transaction processing than in sophisticated decision support and reporting. They found that ERP users were lightly satisfied with reporting and decision support for finance and financial accounting, but were less satisfied with managerial accounting capabilities.

Thus, it is debatable that ERP provides all the information necessary for decision support. According to Davenport (2000) and Kumar & Hillegersberg (2000), ERP may be incomplete (or provide unnecessary information) to users, even though it is widely reported in the literature that ERP promises seamless integration of all the information flowing through a company.

Furthermore, reporting tools available in ERP are normally considered to be limited for decision-making by many adopters. According to Granlund & Malmi (2002), ERP has the capability to generate standard reports, however many firms need non-standard reports for specific patterns. Lack of flexibility of reporting tools and excessive time needed to train staff for amending existing reports or developing new ones were some of the reasons cited for inability of ERP systems to support decision-making (Stanek, Sroka & Twardowski 2004). Carton & Adam (2005) suggested that intelligent decision support can be crucial in determining all information necessary for decision support.
Many researchers examined the perception of decision support characteristics by ERP perspectives in various situations. For example, Holsapple & Sena (2003) examined the extent to which 16 decision support characteristics are exhibited by ERP. The results indicate that adopters perceive decision support characteristics exhibited to a moderate degree by ERP,

and that those that exhibited the greatest degree had the provision of a repository of knowledge for solving problems and mechanisms to facilitate communication within an organisation.

As a case study of Earthgrains, Davenport (2000) described several elements of ERP in addition to those used to create, capture, and store transactional information. Data communications, data access, data analysis, and presentation, assessing data context, synthesising data from other sources, and assessing completeness of data have been suggested. To satisfy users' demands, ERP has evolved from a transitional focus to a more analytical, strategic focus, and to incorporate BI functionality.

Palaniswamy & Frank (2000) described the need for organisations to digest the vast amount of information from the environment and make fast decisions, and the need to "work together and sometimes with other organisations" to make strategic decisions. Thus, it has been suggested that the adopters of new applications should focus on improving the level of decision support provided for their organisations (Holsapple & Sena 2003).

As discussed above, this illustrates a fundamental problem for organisations in using ERP in terms of decision support tools. Li (1999) identified the need for "generating business intelligence (BI)" in the ERP perspective as a primary key to the next generation of ERP with greater decision support. Much research showed that organisations are at different stages in the implementation process ranging from initial strategic analysis implementation options, through completed standard implementations and to the sophisticated exploitation of ERP using advanced knowledge management, decision support, or BIDSA in terms of implementing other systems in add-on functions for ERP of the business organization (Bingi, Sharma & Godla 1999; Davenport 1998; Li 1999).

Selective use of information in managerial decision-making, irrespective of its availability and accessibility, is a typical managerial trait, particularly under conditions of uncertainty. Managers use information selectively to rationalise their decision processes or prefer to use data and decision-making processes "with which they feel comfortable" (Pfeffer 1992). Although ERP systems make information available for managerial decision- making, the application of such information is dependent upon individual managerial preferences and conditions. Managers may miss consequences without using a decision-making model to mask reality with assumed uncertainties embedded in the systems. Thus, there is evidence that ERP needs better decision support features that support decision-making and the use of BIDSA is an important computer-based information system to many firms (ERP user organisations) in solving the performance of poor decision-making.

In the next section, the adoption and diffusion, and factors affecting the adoption of BI and decision support applications (BIDSA) by business firms specifically an ERP perspective are discussed. Also, a theoretical model is reviewed and used for proposing a conceptual model to provide the foundation for empirical investigation of the research questions in this study.

2.7 ADOPTION AND DIFFUSION

Many organisations continue to invest large amounts of resources in new IT, and determining the potential acceptance of these new technologies is important (Chau 1996). If the new IT is accepted and adopted by users, the chances of the system and investments being a success greatly increases (Behrens et al. 2005). With this, technology adoption has been a significant issue for IS research and practice (Brancheau, Janz & Wetherbe 1996; Niederman, Brancheau & Wetgerbe 1991).

A number of theoretical and empirical studies have emerged in the past to address the impact of IT adoption in diverse disciplines and perspectives such as the work by Fisher & Wesolkowski (1998); Beaumaster (2002); Khemthong (2007); Iacovou, Benbasat & Dexter (1995); Byrd & Davidson (2003); and Anderson, Banker & Hu (2003). This is one of the main streams of IS research in the explanation and prediction of IT adoption in organisations. Much empirical research has indicated that the influential factors are different in different countries (Hidding 1998; Xu, Zhu & Gibbs 2004; Zhu, Xu & Dedrick 2003). It is, therefore, important to understand the factors that affect a firm's decision regarding the adoption of innovative systems.

IS researchers have relied on diffusion theory (Rogers 1995) for studying adoption of various innovations (Moore 1995). Various adoption models have been selected as representative of the research conducted with considerable empirical evidence to support them. Particularly, these models cover IS and IT innovations of which BI and decision support applications (BIDSA) can be considered a subset. In IS research, there are a number of theories being used on IT acceptance and use. Reviews and summaries of some of these studies can be found in the literature, such as that by Lucas, Schultz & Ginzberg (1990); Delone & McLean (1992); Lucas Jr. & Spitler (1999); Kripanont & Tatnall (2009) among many others.

Innovation theories include: diffusion of innovations (DOI) (Rogers 1995), theory of reasoned action (TRA) (Ajzen & Fishbein 1980), and technology acceptance model (TAM) (Davis 1986). These provide the primary theoretical foundation for a lot of research projects on IT acceptance and use. However, Kishore (1999) reports that most empirical studies in the IT adoption literature have based on their research on either the diffusion of innovation model (DOI) (Rogers 1995) or the technology acceptance model (TAM) (Davis 1989).

TAM (Davis, Bagozzi & Warshaw 1989), which derived from TRA by Fishbein & Ajzen (1975), has been widely used as a theoretical foundation to explain human behaviour towards the adoption and use of computers (Ditsa 2003). TAM models attempt to explain the relationship between user attitudes, perceptions, beliefs, and actual use of a technology. TAM models postulate two main determinant factors for the behavioural intention to adopt, these being "perceived usefulness (PU)" and "perceived ease of use (PEU)". These constructs are related to the generic "attitude toward behaviour".

Socio-technical approaches posit that technological phenomena should be examined within the contexts in which they are embedded (Orlikowski & Iacono 2001). Moreover, to initiate adopting or to start implementing innovation in an organisation, the IT innovation adoption process involves a sequence of stages that organisations pass through before initiating a new technology. This can explain and predict the influence of a wide range of factors on innovation adoption and implementation decisions. The predictors include factors from the focal social system, the perceived nature of the innovation itself, communication channels, and time. DOI is particularly attuned to the reaction of social factors, organisational culture, communication patterns, and IT innovation characteristics.

In this perspective, Rogers (1995, p 21) defines adoption as:

…the process through which an individual or other decision-making association passes from first knowledge of innovation, to forming an attitude towards innovation, to a

decision to adopt or reject, to implementation of new idea, and to confirmation of this decision.

Innovation diffusion research has also been characterised as rational and interpretive (Beynon-Davies & Williams 2003) and one of the most widely used rational theories, is Rogers' diffusion of innovation theory (Rogers 1995). Many previous studies have built their theoretical premises around Rogers's innovation adoption theory (Rogers 1995), which states that observed adoptions are largely prompted and determined by key innovation attributes that have been communicated to potential adopters. This theory encompasses an innovation (technology) emphasis and has primarily arisen to explain or predict innovation (technology) adoption by an individual or organisation (Tornatzky & Klien 1982).

Consequently, technological innovation adoption has importantly been a major theory for this study. The framework focuses on IT diffusion and adoption in terms of technology (system features), organisational aspects (firm characteristics), and inter-organisational aspects (environmental characteristics) in order to see who might be the real beneficiaries of technology adoption. The following definitions of adoption and diffusion have been chosen to distinguish these two key concepts. "Adoption" is *a decision to make full use of an innovation as the best course of action, whereas rejection is a decision not to adoption an available innovation* (Rogers 1983, p. 21).

There are two levels of adoption. Initially, the innovation must be purchased, adopted, and acquired by an organisation. Subsequently, it must be accepted by the ultimate users in that organisation (Manross & Rice 1986). In this study, it is proposed that several internal and external environmental factors influence different levels of BI systems adoption for an organisation.

As for diffusion, it is the process during which an innovation is communicated through certain channels over time among members of a social system (Rogers 1983). Technology diffusion follows the five broad stages of: initiation, adoption, implementation, evaluation, and integration. Corresponding to the evolutionary nature of BIDSA, the diffusion of BIDSA process integration is viewed as a cyclical, recurring process.

Prior studies have suggested that there are differences in using technologies in business organisations between different regions (Dewan & Kraemer 2000). A study of the role of IT in Australian business shows that misused IT could be an impediment to IT development and implementation (Sohal & Ng 1998). However, BI applications are not widely adopted and implemented in many business sectors in Australia (Foster, Hawking & Stein 2005). Most of the available research relating to BIDSA focuses on technological and operational aspects (Arnott & Pervan 2005; Azvine, Cui & Nauck 2005; Foster, Hawking & Stein 2005; Gibson & Arnott 2003; Lönnqvist & Pirttimäki 2006; Negash, Solomon 2004; Olszak & Ziemba 2006, 2007; Rudra & Yeo 1999; William & William 2003), while there is very little research that considers human, managerial, and strategic factors. It is, therefore, important to understand the factors that affect a firm's decision regarding the adoption of BIDSA.

2.7.1 Theoretical Background

The functional parallels between information systems (IS) adoption and technological innovation adoption have been suggested by several researchers (Kwon & Zmud 1987; McFarlan & McKenney 1982). Thus, the theoretical foundation for much technology adoption research is based on the diffusion of innovations literature (Rogers 1983; Tornatzky & Fleischer 1990; Tornatzky & Klien 1982), which includes reports of studies on the process of technology innovation diffusion and factors influencing technology innovation adoption.

The purpose of this study was to develop a conceptual model and identify factors affecting the adoption and diffusion of BIDSA so the theoretical basis for this study is found in organisational innovation literature and includes innovation theory.

2.7.1.1 Diffusion of Innovation Theory

Rogers (1995, p. 5) defined diffusion of innovation as *the process by which an innovation is communicated through certain channels over time among the members of a social system.* He also identified the four main elements of a diffusion process as: 1) the innovation; 2) communication channels; 3) passage of time and 4) the social system. Rogers (1995, p. 11) defined an innovation as *a process, object, or idea that is perceived as new by an individual or another unit of adoption*.

Innovation has been studied at the level of the industry, the firm and the individual (Damanpour 1991). Thus, this study focuses on innovation at the organisational level, where it is defined as the adoption of a new idea by an adopting organisation (Damanpour 1996) so the innovation in this study is defined in terms of adoption of the BIDSA by ERP user organisations for their analytical information applications.

Communication channels are *the means by which messages get from one individual to another* through mass media and interpersonal channels (Rogers 1995, p. 18). In this study, the diffusion of BIDSA in ERP user organisations refers to the channels through which each ERP user manager learns or gains experience for the use of BIDSA.

Rogers (1983, 1995) related time of adoption to characteristics of the innovation. He identified the five characteristics of an innovation that affect its rate of diffusion as: relative advantage, complexity, compatibility, trialability, and observability. All these factors, except complexity, have a positive relationship with the rate of adoption of technology (Rogers 1995; Zaltman, Duncan & Holbek 1973). Innovation diffusion is faster if potential adopters perceive the innovation to have a relative advantage and be compatible with their practices and needs.

According to Rogers (1995), there are five types of innovation adopters: 1) innovators; 2) early adopters; 3) early majority; 4) late majority; and 5) laggards. Innovators are the fastest adopters while laggards are the slowest adopters. Table 2-2 shows and explains the different types of innovation adopters and their characteristics (Cain & Mittman 2002; Rogers 1995) (see the next page). Many researchers seek to identify key drivers and barriers of IT during initial adoption rather than during implementation (Laage-Hellman & Gadde 1996; Marosszeky et al. 2000). Early adopters have the vision to adopt an emerging technology because of business opportunities or technology needs. In this phase, the supporting tools and products are not matured enough to support the standards. Therefore, there are obstacles in building applications using BI standards. Many BI application companies and system integration firms belong to this category. As to model BIDSA adoption and find factors affecting BIDSA in this study, time refers to the relative earliness of the adoption of BI and information analytical applications by ERP user organisations.

Innovation Adopters and Characteristics	
Categories	**Characteristics**
Innovators	**(Venturesome)** ▪ Venturesome and eager to try new ideas ▪ Cosmopolite ▪ Geographically dispersed contacts ▪ High tolerance of uncertainty and failure ▪ May or may not be respected by peers
Early Adopters	**(Respect)** ▪ Well-respected opinion leadership ▪ Well integrated inn social system ▪ Judicious and successful use of innovation
Early Majority	**(Deliberate)** ▪ Deliberate before adopting new idea ▪ Highly interconnected with a peer system ▪ Just ahead of the average
Late Majority	**(Sceptical In general)** ▪ Approach innovations with caution and skepticism ▪ Responsive to economic necessity ▪ Responsive to social norms ▪ Limited economic resources ▪ Low tolerance for uncertainty
Laggards	**(Traditional)** ▪ Hold on to traditional values ▪ Relatively isolated ▪ Precarious economic situation ▪ Suspicious of new innovations and change agents

Source: Adapted from Rogers (1995) and Cain & Mittman (2002)

Table 2-2: Innovation adopters and characteristics

Rogers (1995, p. 23) defined a social system as *a set of interrelated units that is engaged in joint problem-solving to accomplish a common goal*. The members of units of a social system may be individuals, informal groups, organisations, and/or subsystems. At the organisational level, the unit of adoption is the organisation while the social system is the organisation's external environment. Thus, in this study, the unit of adoption is the ERP user firm in Australia, and the social system is the ERP user organisations' external environment such as competition, customers, and technology support.

2.7.1.2 Dimensions of the innovation process

As pointed out by Damanpour (2002), organisational change takes place when organisations evolve from old behaviours and methods of operations to new ones. The difference between the current states prior to change to the future state of an organisation can be a consequence of the generation or adoption of innovations. This means that organisational innovation is a subset or sub-process of organisational change (Damanpour 2002).

(Damanpour 2002, p. 1726) distinguished two dimensions of the innovation process: 1) generation; and 2) adoption. The generation of an innovation is *a process that results in the creation of an innovation that is new to at least one organisational population*. If the outcome of the generation process is then acquired by another organisation, the second organisation goes through another process, the adoption of innovation. The adoption of innovation process is *a process that results in the inclusion of an innovation that is new to the adopting organisation*.

The adoption process concerns a sequence of stages that a potential adopter of an innovation passes through before acceptance of the new process, product or idea. Rogers (1995, p. 21) defines the adoption process as *the process through which an individual or other decision-making unit passes from first knowledge of an innovation, to forming an attitude towards the innovation, to a decision to adopt or not adopt, to implementation of the new idea, and to confirmation of this decision*. The innovation process can be considered a success to the extent that innovation is accepted and integrated into the organisation (Rogers 1995; Zaltman, Duncan & Holbek 1973). With respect to organisational adoption, two main stages are pointed out: initiation and implementation (Tornatzky & Klien 1982; Zaltman, Duncan & Holbek 1973).

Rogers (1995, p. 21) claimed that *adoption is a decision to make full use of an innovation as the best course of action available*. In the initiation stage, the organisation becomes aware of the innovation, forms an attitude towards the new product or idea and evaluates it. In the implementation stage, the organisation decides to purchase and make use of the innovation (adoption and continue use). Thus, in this study, the full and actual adoption of innovations in an organisational context implies that adoption occurs within the ERP user organisations and is integrated into ongoing business practices.

2.7.1.3 Innovation Characteristics

The characteristics of an innovation can be discussed along four dimensions (Poutsma et al. 1987 cited in Thong 1999): 1) product and process innovations; 2) radical and incremental innovations; 3) technology-push or market-pull; 4) planned and incidental innovations.

1) Product and Process Innovations

Product innovation involves the development, production, and dissemination of new consumer and capital goods and services while process innovations are innovations that improve the production process through the introduction of new methods, machines or production systems. Damanpour (1996) noted that *process innovations* are: (1) less observable and perceived to be relatively less advantageous, as they are merely related to the delivery of outcomes, rather than being the outcome themselves; and (2) more difficult to implement, as their successful implementation depends upon more widespread changes in organisational structure and administrative systems.

2) Radical and Incremental Innovations

Radical innovations are innovations that produce fundamental changes in the activities of an organisation and large departures from existing practices. However, incremental innovations are minor improvements or simple changes in current technology.

3) Technology-Push or Market-Pull

Innovations can occur because there is technology-push or market-pull. Technology-push refers to an innovation that is developed and offered in a mature form on the capital-goods market. Under pressure exerted by the completing suppliers and the ascribed superiority of the new innovation, the market is required to absorb the new innovation. In a market-pull stage, a social need is felt, acknowledged, and translated into technical demand. In respond to this demand, a new technology is developed.

4) Planned and Incidental Innovations

Planned innovations are innovations that are carried out because of a plan where the business aims to control the market through its innovation. Innovations are considered to be incidental when they occur as a specific reaction of a business to new market demand.

Information systems (IS) can be considered as a technological innovation, and IS are radical innovations because radical innovations cause fundamental changes that represent revolutionary changes in technology, while incremental innovations are minor improvements or uncomplicated changes in current technology (Dewar & Dutton 1986). Fundamental parallels between technological innovation and IS adoption have been suggested by many IS researchers (Keen & Morton 1978; Kwon & Zmud 1987; McFarlan & McKenney 1982). For example, data warehouse as BIDSA infrastructure which belongs to the category of a radical infrastructure type technology innovation provides a foundation for the development of a number of other value-added IT applications (Duncan 1995). Data warehouse provides a foundation for integrating a disparate set of internal and external data sources, enabling enterprise-wide data access and sharing, enforcing data quality standards, addressing business issues, providing enterprise decision support, and promoting strategic thinking through CRM, data mining, and other front-end BI applications (Wixom & Watson 2001).

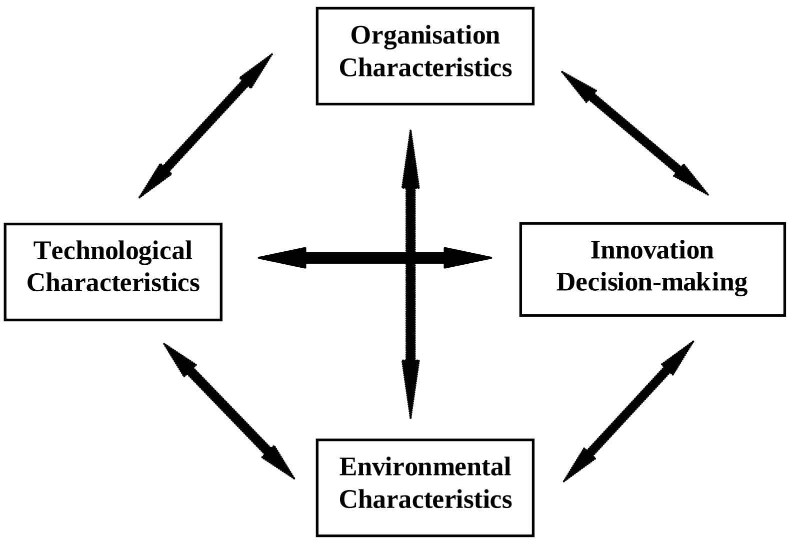
Therefore, the adoption of BIDSA is the result of a radical innovation. For ERP user organisations, the adoption of BIDSA is likely to cause change in work procedures of different business functions, knowledge of specific system applications and to increase computer-network based systems among the employees. Thus, not only is an innovation a renewal by means of technology, but it can also be a renewal in terms of thought and action (Poutsma et al. 1987 cited in Thong 1999).

2.8 FACTORS AFFECTING TECHNOLOGICAL INNOVATION ADOPTION

The innovation adoption model by Rogers (1995) has been proposed to explain the principles of the adoption of IT innovations. Clegg et al. (1997) reported in their findings that 80-90% of IT investments do not meet their performance objectives, and reasons for this rarely purely technical in origin. The context of technical change means the way in which IT is adopted, developed, and implemented, a range of human and organisational factors, and the roles of managers and end-users are identified as a critical area affecting overall organisational performance.

Previous technological innovation researchers have identified various groups of variables that are possible determinants of organisational adoption of an innovation. For instance, Tornatzky & Fleischer (1990) proposed a “technological innovation model” which consisted of three contexts that affect adoption and implementation of technology in firms: 1) organisational context; 2) technological innovation context; 3) external environment context. By applying this model, (Chau & Tam 1997) insisted that the theoretical framework suggested by Tornatzky and Fleischer is “a useful starting point” in studying technological innovation adoption.

Particularly for IS adoption relating to decision support applications (e.g. DSS, EIS. KMS), to study the adoption of technological innovation in an organisation, Zailani, Ong & Shahnon (2006) declared that the influencing factors include technological, organisational, and environmental characteristics. They noted that these contexts have positive influences directly on the adoption of IS. Figure 2-6 below illustrates the facets of the model proposed by Tornatzky & Fleischer (1990).



Source: Adapted from Tornatzky & Fleischer’s (1990) framework.

Figure 2-6: The context of technological innovation

Thong (1999) proposed an integrated model of IS adoption in small businesses. Three elements for information system adoption can be identified as: 1) characteristics of the organisational and decision maker characteristics); 2) Characteristics of the technological innovation; and 3) characteristics of the environment. Afterwards, Kamal (2006) proposed related factors and modelled IT innovation adoption. The constructs can divide the organisational contexts into organisational and support as: 1) technology factors; 2) organisational and support factors; and 3) external forces.

From this literature, Tonatzky & Fleischer's (1990) model and Thong's (1999) elements as well as Kamal's (2006) components are the basis for this study in developing the conceptual model. In order to acknowledge a better understanding regarding factors affecting the use of BIDSA, three main characteristics of technological innovation adoption are reviewed and presented as follows: 1) technological innovation; 2) organisations and supports; 3) environment.

2.8.1 Characteristics of the Technological Innovation

Based on an analysis of the organisational innovation literature, technological innovation characteristics are widely and frequently used as a key determinant of innovation adoption. As previously mentioned, Rogers (1983, 1995) identified five attributes of an innovation that can influence adoption: 1) relative advantage; 2) complexity; 3) compatibility; 4) trialability; 5) observability. With other rational diffusion theorists such as (Agarwal & Prasad 1998; Moore & Benbasat 1991), the attributes mentioned above are certain characteristics of innovations which affect their rate of adoption. However, more importantly it reveals that factors and barriers of technology transfer can block a successful adoption (Baskerville & Pries-Heje 2001). Tornatzky & Fleischer (1990) identified perceived barriers and perceived benefits as technological innovation characteristics. A further two discussed by Herbig & Day (1992) are cost and risk.

As a consequence of the studies, researchers applied different innovation attributes when testing the adoption of an innovation by an organisation. The perceived innovation characteristics presented by Rogers (1995) have been discussed extensively. Studies undertaken by Chen (2003), Kendall et al. (2001), and Menachemi, Burke & Ayers (2004) reveal that the five attributes of innovation characteristics proposed by Rogers (1995) influence the adoption of information systems. However, a meta-analysis of research in this area, Tornatzky & Klien (1982) found that out of as many as 25 innovation attributes studied by researchers, there are three items: 1) relative advantage (benefit); 2) complexity; and 3) compatibility that usually are consistently related to adoption.

For example, using the same attributes proposed by Rogers (1995) and Ramamurthy, Sen & Sinha (2008b) suggested and proposed that relative advantage and complexity are positive key determinants of a specific IS application (data warehouse). Thompson, Lim & Fedric (2007) indicated that relative advantage and compatibility are positively related to the adoption of human resources information systems (HRIS). Many studies have revealed that perceived barriers and perceived benefits are the most important groups of innovation characteristics affecting the adoption of innovation in firms (Chau & Tam 1997; Iacovou, Benbasat & Dexter 1995; Kumar, Maheshwari & Kumar 2002; Scupola 2003)

2.8.2 Characteristics of Organisations

Organisation characteristics including support are believed to influence innovation in organisations (Grover & Golslar 1993). These characteristics have also been used as key determinants of technological innovation adoption. Previous studies have investigated a range of organisational characteristics. For example, Doll (1985) pointed out that top management is responsible for providing general guidance of IS activities. Lee & Shim (2007) also suggested that perceived benefits are positively related to technology adoption. Gatignon & Roberston (1989) and (Rogers 1995) showed that the support by top managers would also affect the adoption of new technology. Prior research suggested that top management support influences the successful adoption and implementation in integrated IT solutions (Grover 1993; Ngai & Gunasekaran 2004; Ramamurthy, Sen & Sinha 2008a). For example, Rai & Bajwa (1997) examined organisational factors including top management support and organisation size affecting the adoption of EIS. They suggested that top management support is a positive factor.

A large organisation has more resources for creating new strategy. Grover (1993) and Huang, Hung & Yen (2005) discovered that organisational scale was the major factor that affects the adoption of new IT. Thong (1999) identified three organisational attributes: 1) business size; 2) employee's information system knowledge; and 3) information intensity, and found that organisational characteristics influence the adoption of IT in small businesses. Buonanno et al. (2005) found that business size has a significant effect on ERP adoption among SMEs and large companies. Numerous other literatures have confirmed that organisational size is one of the key factors to new information technology (Premkumar & Roberts 1999; Thong & Yap 1995).

Relating to innovativeness of IT, Cohen & Levinthal (1990) pointed out that an organisation needs to recognise the value of new (external and internal) information for making economic benefits. BIDSA technology is a type II technology, technology to foster innovative learning (Maddux et al. 1997) including database management systems (Ball, Dambolena & Hennessey 1987), computing network (Gurbaxami 1990), software development process technologies (Nilakanta & Scamell 1990), and information technology (Gurbaxami & Mendelson 1990). A study by Fichman (1992) suggested that the ability of absorptive capacity of organisations to adopt new innovations is necessary. For example, Ramamurthy, Sen & Sinha (2008) found that organizational absorptive capacity is an important factor in adopting data warehousing technology.

In addition, it would be helpful to adopt IT only after managers understand internal needs. Prior research Zmud (1984) showed that the internal need of an organization is an important factor which affects the adoption of a new information technology (IT). For example, Premkumar & Ramamurthy (1995) found that the organizational factors such as internal need and top management support influence a firm's EDI adoption decision. The adoption of new technology actually results from internal need (Grover & Golslar 1993; Hwang et al. 2004; Li et al. 2005; Watson & Haley 1997).

2.8.3 Characteristics of the Environment

Environmental characteristics are another force driving organisations to adopt IT. These are important factors that have been studied in much previous research (Grover 1993; Holsapple & Joshi 2000; Kwon & Zmud 1987; Thong 1999). The external environment context explains the characteristics of external factors that could present opportunities and constraints for technological innovation adoption. It is implied that in more turbulent and unstable environments, a more rapid adoption of innovative technology should be carried out. For instance, as pointed out by Chau & Tam (1997), due to market uncertainty, market conditions represent a major factor in the innovation process. A company's desire to be ahead of the competition is a major factor in adopting IT (Kunnathur, Ahmed & Charles 1996). A company that is dominant in a specific market tends to be a leader, is responsible for IT innovations or is very fast to adopt what has been introduced by competitors (Leonard-Barton 1991).

Increased external competition usually propels an organisation to search for new ways to increase its productivity and seek competitive advantage (Themistocleous, Irani & Kuljis 2004). Competitors are actually important drivers in adoption of innovative technology (Waarts, Everdingen & Hillegersberg 2002). Competitive pressure has been shown in a study to have an influence on the adoption of information technology (Hannan & McDowell 1984; Iacovou, Benbasat & Dexter 1995; Levin, Levin & Meisel 1987). For example, Hwang et al. (2004) identified and investigated that environmental attributes including degree of business competition and selection of vendors are important factors for the adoption of data warehouse. Reports indicate that competitive pressure was an important factor for the company to adopt data warehouse.

However, when good coordination exists between organisations and their IT vendors, the organisation always favours the adoption of innovative adoption (Gatignon & Roberston 1989). Selection of implementation partners is very important because these organisations partner and facilitate the organisation in their adoption, implementation, and stabilising of the applications. As well, even with today’s state of the art, no single enterprise system meets all the information-processing needs of the majority of organisations (Davenport 2000). Kumar, Maheshwari & Kumar (2002) found that a group of external factors affect ERP adoption. Results indicated that implementation partners are a key factor affecting IT adoption, particularly, it showed that outsourcing skills from consultants came out as a widely accepted method in ERP adoption. Vendor selection in particular is an important consideration. Some past studies (Hwang et al. 2004; Kimball 1996) points out that if the enterprise decides to outsource the implementation of BI applications, then they must be careful in selecting the vendors.

Various factors have been identified in previous studies as influencing technological innovation adoption in an organisation. As previously mentioned, the theoretical foundation for much technology adoption research has been based on the diffusion of innovation literature (Kamal 2006; Rogers 1995; Tornatzky & Fleischer 1990; Tornatzky & Klien 1982).

Thus, a desired conceptual model in order to understand technology adoption in an organisation has been developed from the models that belong to Rogers (1995), Tornatzky & Fleischer (1990), and Thong (1999), as well as Kamal (2006). The factors identified in the above studies can be grouped into the three main categories of factors: 1) technological innovation; 2) Organisational and support; and 3) environmental as shown at Table 2-3 below.

A Summary of Categories of Factors Affecting Technological Innovation Adoption in Organisations Identified by Previous Studies			
Authors	**Organisational and supports**	**Environmental**	**Technological Innovation**
Grover (1993)	YES	YES	YES
Iacovou, Benbasat & Dexter (1995)	YES	YES	YES
Chau & Tam (1997)	YES	YES	YES
Thong (1999)	YES	YES	YES
Kendall et al.(2001)			YES
Kumar, Maheshwari & Kumar (2002)		YES	
Chen (2003)			YES
Bradford & Florin (2003)	YES	YES	YES
Scupola (2003)	YES	YES	YES
Hwang et al.(2004)	YES	YES	
Menachemi, Burke & Ayers (2004)			YES
Kamal (2006)	YES	YES	YES
Zailani, Ong & Shahnon (2006)	YES	YES	YES
Thompson, Lim & Fedric (2007)	YES	YES	YES
Ramamurthy, Sen & Sinha (2008)	YES		YES

Table 2-3: A summary of categories of factors affecting technological innovation adoption

Then table 2-4 below gives on overview of major studies that have investigated explanatory variables for technological innovation adoption in an organisation.

A Summary of Explanatory Variables for Organisational Innovation Adoption From Previous Studies				
Authors	**Research Setting**	**Explanatory Variables (Factors)**	**Key Findings**	**Methodologies**
Grover (1993)	Interorganisational System (IOS)	▪ IOS Factors ▪ Environmental Factors ▪ Organisational Factors ▪ Support Factors	▪ IOS (compatibility, relative advantage, complexity) ▪ Support (top management support and champion)	Survey Questionnaires
Iacovou, Benbasat & Dexter (1995)	Electronic Data Interchange (EDI)	▪ Perceived Benefits ▪ Organisational readiness ▪ External Pressure	▪ Perceived Benefits (moderate relationship) ▪ Organisational readiness (weak relationship) ▪ External Pressure (strong relationship)	Interviews
Rai & Bajwa (1997)	Executive Information Systems (IS)	▪ Organisation size ▪ Environmental Uncertainty ▪ Top Management Support ▪ IS Characteristics and Support	▪ Environmental Uncertainty ▪ IS Support	Survey Questionnaires
Chau & Tam (1997)	Open Systems	▪ External Environment Contexts ▪ Organisational Contexts ▪ Technological Contexts	▪ Technological Contexts (perceived barriers; perceived Importance of compliances to Standards, interoperability, and interconnectivity)	Interview Survey
Thong (1999)	Information System (IS)	▪ CEO Characteristics ▪ Organisational Characteristics ▪ Environmental Characteristics ▪ Perception of IS Attributes	▪ CEO Characteristics; ▪ Organisational Characteristics ▪ Environmental Characteristics	Survey Questionnaires
Chengalur-Smith & Duchessi (1999)	Client-Server Technology	▪ External Environment Contexts ▪ Organisational Contexts ▪ Technological Contexts	▪ Environment (competitive position) ▪ Technological Contexts (scale of clients)	Survey Questionnaires
Kendall et al. (2001)	Electronic Commerce	▪ Relative Advantages ▪ Compatibility ▪ Complexity ▪ Trialability ▪ Observability	▪ Relative advantage, compatibility, trialability	Survey Questionnaires
Kumar, Maheshwari & Kumar (2002)	Enterprise Resource Planning (ERP) Systems	▪ Organisational Contexts ▪ Environmental Contexts ▪ Characteristics of Expected Benefits	▪ Organisation (size, sector, time); ▪ Environment (outsourcing skills from consultants)	Survey Questionnaires/ Interviews
Scupola (2003)	Electronic Commerce (E-Commerce)	▪ Organisational Contexts ▪ Technological Contexts ▪ External Environmental	▪ Environment (government intervention, public administration; and external pressure from customers, suppliers, and competitors)	Interviews
Bradford & Florin (2003)	ERP Systems	▪ Innovative Characteristics ▪ Organisational Contexts ▪ Environment Contexts	▪ Organisation (Top management support, training); ▪ Environment (competitive pressure)	Survey Questionnaires
Hwang et al. (2004)	Data Warehouse (DW) Technology	▪ Organisational Contexts ▪ Project Planning Dimensions ▪ External Environmental	▪ Organisation (top management, size, champion, internal needs; ▪ Environment (competitive pressure)	Survey Questionnaires
Bounanno et al. (2005)	ERP Systems	▪ Organisational Contexts ▪ Business Factors	▪ Organisation (company size)	Survey Questionnaires/ Interviews
Lee & Shim (2007)	Radio frequency identification (RFID)	▪ Technology Push/ Need Pull ▪ Organisational Readiness ▪ Presence of Champions	▪ Technology Push (Perceived Benefit, Vendor Pressure) ▪ Need Pull (Performance Gap, Market Uncertainty) Presence of Champions	Survey Questionnaires
Thompson, Lim & Fedric (2007)	Human Resources Information Systems (HRIS)	▪ Environment Contexts ▪ Organisational Contexts ▪ Innovation Contexts	▪ Organisation (top management support)	Survey Questionnaires
Ramamurthy, Sen & Sinha, (2008)	Data Warehouse (DW) Technology	▪ Innovation/Technology Factors ▪ Organisational Factors	▪ Innovation/Technology (relative advantage, complexity); ▪ Organisation (commitment, size, absorptive capacity)	Survey Questionnaires

Table 2-4: A summary of explanatory variables for organisational innovation adoption

2.9 THE ADOPTION OF BIDSA BY BUSINESSES

Several previous studies in relation to data usage organisations have investigated the adoption of information technology (IT) in various situations in different types of organisations. For example, Lee & Runge (2001) examined the use of IT in small businesses by using an innovation adoption model adapted from Rogers (1983)'s model. They reported that three antecedents influenced IT adoption in a business environment: 1) the owner's perception of relative advantage of using IT; 2) social expectations of IT use; and 3) the owner's innovativeness in managing their own business.

Perceived ease of use has also been discussed as an important indicator for IS acceptance by users or decision makers (Adams, Nelson & Todd 1992; Davis 1989). According to the Technology Acceptance Model (TAM) proposed by Davis (1989), the complexity of data processing for decision support has a dual effect, direct as well as indirect, on users to the use of data warehouse applications. Gardner (1998), Kimball et al. (1998), and Gray & Watson (1997) pointed out that ease of use is also a determinant of the perceived system and service quality of the use of data warehouse in terms of the systematic management of metadata (database) and its tight integration with computing processes, access authorisation, and ability to locate data.

Caldeira & Ward (2002) investigated the successful adoption and use of IS/IT in the manufacturing industry. They found that top management perspectives and attitudes towards IS/IT adoption and use play an important role in the development of internal IS/IT competencies and provide an important contribution to the development of a context that enables IS/IT success.

In particular, Wöber & Gretzel (2000) investigated decision support applications relating to tourism managers' adoption of marketing decision support systems in the tourism industry, and found that the actual use of a decision support applications (e.g. DSS, KMS) has a positive perception of benefits and advantages. This implies that tourism organisations should focus on user support, especially more detailed information on system content and functionality.

Hung et al. (2005) examined the factors in adopting a KMS for the pharmaceutical industry in Taiwan, and found seven factors to be critical: a benchmarking strategy and knowledge structure; the organisational structure; information technology; employee involvement and training; the leadership and commitment of senior management; a learning environment and resource control; and evaluation of professional training and teamwork.

Watson et al. (2006) investigated BIDSA in terms of technology architecture and organisational processes of the airline industry in contemporary real-time business intelligence and found that applications that can leverage real-time BIDSA by impacting business process to create value to an organisation of decision support. It is implied that benefits for IS users had positive perceptions of BIDSA.

Ikart & Ditsa (2004) examined the factors affecting the adoption and usage of EIS by executives in Australia. The results suggest that organisational contextual factors such as cultural, social and individual factors are of vital importance in explaining adoption and the use of EIS. They also suggest that the experience in EIS such as computer-based information systems (CBIS) and significance of knowledge are positively related to the use of EIS.

Ou & Peng (2006) investigated the ability of BIDSA in terms of process-driven decision making using Knowledge Based Business Intelligence System (KBBIS) by using a model proposed by Baïna, Tata & Benali (2003). The results indicate that with the implementation of case-based reasoning and rule-based reasoning technology, the process models can be built and managed efficiently and provide a strategy for knowledge management in business intelligence systems. It is implied that relative advantages of IT will be beneficial.

Xu & Quaddus (2005) investigated adoption and diffusion of knowledge management systems (KMS) in Australian firms and found that role of individual factors and task complexity influence the perceived usefulness of KMS. Kerr (2004) investigated the factors affecting the development and adoption of knowledge based decision support systems within the Australian dairy industry. He reported that cultural, political, educational, and age factors as well as individual characteristics of IT influenced the rate of adoption.

Further, Wong & Aspinwall (2005) explored the factors for knowledge management (KM) adoption in the SME sector. They found that the top five factors for adopting KM involve 1) management leadership and support; 2) culture; 3) strategy and purpose; 4) resources and processes; and 5) activities.

Mostly related to BIDSA, Hwang et al. (2004) examined the various factors playing crucial roles in the adoption of a data warehouse in a banking industry. The results suggest that organisational dimension (top management support, effect of champion, internal needs, and size of organisations) and external characteristic (competitive pressure) affect the adoption of data warehouse technology.

Ramamurthy, Sen & Sinha (2008) investigated the key determinants of data warehouse adoption in the United States. The results from this model suggest that relative advantage and complexity as well as commitment, company size, and absorptive capacity are the main innovation characteristics of the adoption of innovation.

However, over the past decade, application or technology software selection has become an active area of research due to its complex and imprecise nature. A sociotechnical innovation, which is typically a technology application package, is licensed for use to a client organisation. This type of package is an application (e.g. BIDSA) that is sold as being able to automate specific business processes designed for organisations.

Lin, Huang & Cheng (2007) and Lin, Pervan & Mcdermid (2007) stated that consideration given to both technological and managerial criteria to adopt and select system applications is significant. IS/IT adoption can be understood with the key determinants as an organisation's decision to acquire a specific technology and make it available to target users for their task. Providing a comprehensive review of the adoption of technological applications is also important.

Various potential factors impacting on innovation have increased significantly as the process of IT adoption and use is critical to deriving the benefits of IT (Karahanna, Straub & Chervany 1999). For example, Karsak & Ozogul (2009) indicated that a decision-making approach for the application of ERP selection to adopt requires organisational characteristics and technological contexts as well as interactions from inside and outside organisation (environmental) to be taken into account.

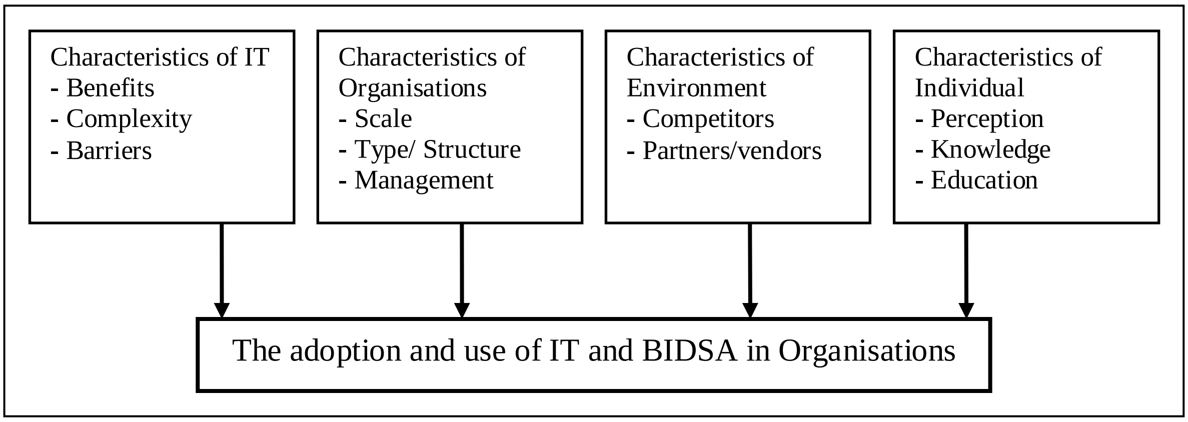
Many previous studies have investigated the adoption of socio technical applications relating to BIDSA in different types of industries in various situations. For example, Buonanno et al. (2005) examined factors affecting ERP system adoption in SMEs and large companies. The result shows that company size is crucial to large organisations. However, only structural and organisational factors are major reasons for adoption in SME.

Russell & Hoag (2004) applied Rogers (1995)' model to study the adoption of supply chain management (SCM) systems. Results indicate that several social and organisational factors do affect adoption success. The factors include user's perceptions of innovation, the firm's culture, the types of communication channels used to diffuse knowledge of innovation, and various leadership factors.

Chen & Wang (2006) analysed the adoption of customer relationship management systems (CRM) and showed that organisational support, management support, and the objectives of CRM implementation are crucial to the success of CRM adoption.

Thompson, Lim & Fedric (2007) recently examined the adoption and diffusion of human resources information systems (HRIS) in Singapore. Their results indicate that organisation size has a significant relationship with the extent of HRIS adoption and that top management has a moderately significant relationship on its adoption.

Many different issues have been reported in the literature on the diffusion of IT and BIDSA in organisations. Factors investigated in several studies can be separated into four groups: 1) characteristics of IT; 2) characteristics of the organisation; 3) characteristics of the environment; 4) characteristics of the individual. Figure 2-7 provides a summary of these factors affecting technology adoption from related BIDSA literature.



Sources: Adapted from Wöber & Gretzel (2000); Darmawan & Keeves (2002); Hwang et al. (2004); Russell & Hoag (2004); Buonanno et al. (2005); Hung et al. (2005); Chen & Wang (2006); Watson et al. (2006); Ou & Peng (2006); Ramamurthy, Sen & Sinha (2008)

Figure 2-7: Factors identified from many types of businesses relating to BIDSA affecting technology adoption

2.10 DEGREE OF ADOPTION OF “BIDSA”

The levels of BI and decision support application (BIDSA) adoption have been described in a number of studies illustrating the transition from the use of personal decision support systems to real-time, interactive access to data, allowing manipulation and analysis of critical information. For example, Gibson and Arnott (2003) defined the level of BI framework using five levels of capabilities ranking from personal or group decision support, executive information systems, data warehousing, intelligent systems (e.g. artificial intelligence, neural networks), and knowledge management.

In contrast, McDonald (2004) further attempts to classify the BI adoption in terms of solutions. The effectiveness of BI solutions is reliant on the underlying data structure. His classification includes:1) BI infrastructure which represents operational systems, transforms, consolidates, and aggregates data in readiness for reporting for decision-making; 2) Business Performance Management (BPM) which refers to the use of data in the previous stage to provide feedback for management on key performance indicators (KPI); 3) Decision Enablement which refers to the automation of decisions using data from a knowledge repository; and 4) Business Activity Monitoring (BAM) which refers to processes to monitor for changes or trends indicating opportunities or problems, and helping managers to take corrective action.

Foster, Hawking & Stein (2005) and Hawking, Foster & Stein (2008) categorised the degree of BI system adoption of Australian ERP firms into four levels: 1) business information warehouse (refers to data warehouse used); 2) advanced planner and optimiser (refer to SCM used); 3) customer relationship analytics (refer to CRM analytics used); and 4) strategic enterprise management (refer to real-time monitoring applications used).

According to the discussion above, it is implied that the level of BIDSA adoption and implementation can be explained using levels of capabilities rankings from “basic capability of decision support characteristics” to “being able to monitor problems and provide multi-business solutions in real-time. Level 1 is an organisation with basic decision support and infrastructure characteristics of a relational database, but no advanced capabilities. Level 2 represents an organisation with data warehouse for data integration while BI with analytics applications represents level 3. Level 4 refers to an organisation that is able to extend the capabilities of business functions (e.g. SCM, CRM). The last level represents an organization that comes with all level with near real-time monitoring.

In this study, two stages of adoption of BI and decision support based applications by business organisations who are implementing ERP are: 1) an early adopter group; and a non-early adopter group. These have been identified based on the literature utilising the work of Rogers (1995) and also prior studies on decision support applications and BI systems (Foster, Hawking & Stein 2005; Hawking, Foster & Stein 2008; Negash, Solomon 2004).

For the purpose of this study, "early adopters" are defined as ERP user organisations that have data integration level: data warehouse, ETL, data mart etc for data acquisition and storing, analytic applications (e.g. OLAP, data mining) for versatile analyses of data and other extended application systems (e.g. CRM, SCM, BI real-time) for various decision-making. The definition of "non-early adopters" is ERP user firms that have only a basic decision support approach (e.g. DSS, KMS, EIS); the firms that have a basic decision support approach and relational database for helping in making decisions; and the organisations that have BI infrastructure and business analytics for creating strategies for business purpose.

2.11 SUMMARY

In summary, this chapter has described the importance and the success of the use of BIDSA in business organisations in Australia particularly for ERP user organisations. The purpose of this chapter was to describe the theoretical underpinnings of this research study. Studies related to the adoption of technological innovation in an organisation and ERP user businesses were reviewed. The finding of a comprehensive analysis of all factors affecting the use of BIDSA derived from extensive analysis of secondary data sources, mainly existing adoption and diffusion literature and the literature on the diffusion of ICTs and decision support applications.

In particular, several aspects of the literature have been chosen as the basis for the conceptual model described in the next chapter. There are based on Tornatzky & Fleischer's (1990) model: 1) technological innovation (Rogers 1995; Thong 1999); 2) organizations (Kamal 2006; Ramamurthy, Sen & Sinha 2008; Thong 1999); and 3) environment (Hwang et al. 2004; Kamal 2006). These perspectives have developed analytical and empirical models which describe and/or predict the adoption decision and extent of diffusion of IT within an organization.

Consistent with the relevant literature, the BIDSA adoption construct is incorporated into the proposed theoretical model, as this construct is increasingly being recognised as playing an important role in the adoption of organisational innovation (Gatignon & Roberston 1989; Kwon 1990; Rogers 1995; Tornatzky & Fleischer 1990). This is presented to fill the gap of BIDSA adoption. In summary, this chapter has described the importance and the success of the use of BIDSA in business organizations in Australia particularly for ERP user organizations.

The next chapter will present a conceptual model for the adoption of BIDSA by Australian firms along with complement reviews of exploratory study integrated into the proposed model. This is done to establish the factors affecting BIDSA adoption by organizations in Australia with an ERP perspective.

CHAPTER 3

CONCEPTUAL FRAMEWORK

3.1 INTRODUCTION

As mentioned in the previous chapter, this chapter discovers providing the theoretical concepts in developing decision support applications and organisational innovations. Business intelligence and decision support applications (BIDSA) are not widely adopted and implemented in businesses in Australia and the factors that affect the adoption of BIDSA have not been fully investigated. In this chapter, the focus is on a conceptual model for understanding the issues surrounding BIDSA adoption derived from diffusion of innovations and evaluating the factors affecting the adoption of BIDSA in Australian business organisations.

3.2 A CONCEPTUAL MODEL OF ADOPTION OF BIDSA BY ERP USER ORGANIZATIONS

Based on assessment of these prior studies, it is clear that the factors affecting the adoption and implementation of BIDSA by ERP user organisations in Australia have not yet been fully investigated (Grover 1998; Hawking, Foster & Stein 2008; 2004; Ramamurthy, Sen & Sinha 2008; Xu & Quaddus 2005). As Tornatzky & Klien (1982) pointed out, studies of organisational adoption should examine multiple explanations of adoption behaviour to assess the influence of different forces. Specifically, Newell, Swan & Galliers (2000) suggested that diffusion of innovation theory can be used positively to examine information communication technology and complex information technology adoption in business organisations.

Mistillis, Agnes & Presbury (2004) provide another example for suggesting use of this theory in order to determine ICT adoption. Thus, a conceptual model for the adoption of BIDSA will incorporate those factors affecting the use of IT in an organisation; a concept derived from the organisational innovation and specific ERP user organization literature.

3.2.1 Pilot Study to Help Build the Conceptual Framework

As there was no previous research on the adoption of BIDSA with the ERP perspective in Australia (see Table 2-4), an exploratory study was employed to supplement the literature review. Therefore, during the month of August 2007 at a conference of the SAP Australian User Group (SAUG) summit 2007, short semi-structured interviews were conducted with representatives from twenty ERP user organisations in Australia. Each interview took approximately ten to fifteen minutes to complete. Participants were at IT executive level (e.g. CIO, IT executives, IT project managers, IT managers). The short interview questions (see Appendix A1) were designed to determine:

- General information about firm demographics,
- Main reasons for, and problems influencing the adoption of BIDSA by ERP users in Australia,
- Benefits and cost of the adoption of BIDSA by the ERP sector in Australia, and
- Factors expected in Australia that support the use of BIDSA

The results of these interviews (e.g. opinions, recommendations, and experiences) (see Appendix A2) provided direction as to what factors were important for firms in Australia and how these factors were assessed by occupants of these senior management positions.

3.2.2 Proposed Research Variables

The proposed conceptual model for this study was developed incorporating key variables derived from a review of the research literature on innovation adoption in organisations and from the results of the exploratory in-depth interviews in Australia. In table 3-1, the research variables used in this study are summarised.

Research Variables Categorised for the Study		
Groups of Factors	**Theoretical Contexts**	**Variables**
Organisational Factors	Organisational Structure and Process	**Top Management Support** **Organisational Size/ Resources** **Absorptive Capacity** **Internal Need**
Technological Factors	Technological Contexts	**Perceived Benefits** **Task Complexity** **System Compatibility**
Environmental Factors	Organisational Environment	**Selection of Vendors** **Competitive Pressure**
Sources: Group of factors (adapted from Tonatzky & Fleischer 1990; Thong 1999; Kamal 2006) : Research variables (adapted from organisational innovation adoption, decision support and ERP system literature and the results of preliminary study (short interviews))		

Table 3-1: Research variables in the study

In this study, the proposed conceptual model incorporates three key groups of factors: organisational factors, technological innovation factors, and environmental factors based on Tornatzky & Fleischer (1990).

The organisational factors consist of the inherent characteristics of the ERP user firm- top management support, organisation size, absorptive capacity, and internal need. The technological innovation factors consist of three aspects: 1) perceived benefits; 2) complexity; 3) compatibility. The environmental factors for the organisational environment consist of two aspects: 1) competitive pressure; and 2) selection of vendors, which represents organisational environment theory.

This model proposes that there is a direct relationship between these factors and the adoption of BIDSA by business firms. The degree of adoption of BIDSA will be measured in two levels: 1) early adopter; and 2) non-early adopter ERP users. Figure 3-1 below shows a conceptual model of adoption of BIDSA by ERP perspectives.

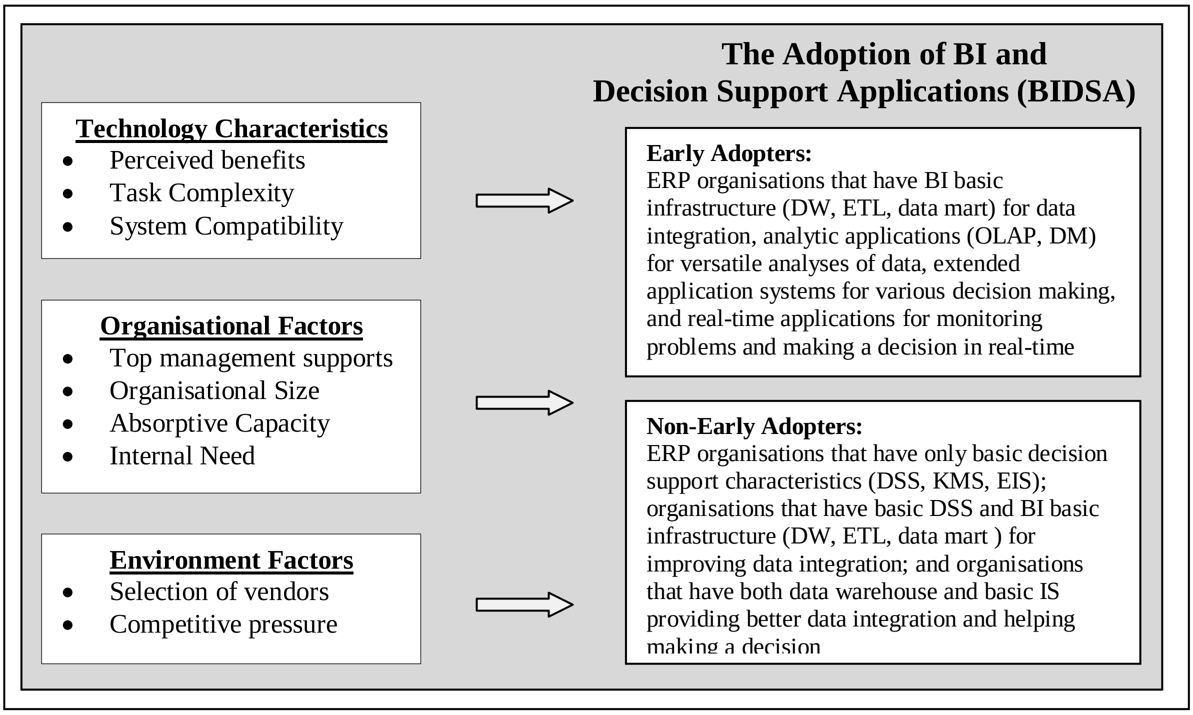


Figure 3-1: A conceptual model of adoption of BI and decision support applications (BIDSA) by ERP user organizations

Remark: For an explanation of the abbreviation used in this model (e.g. BI, BIDSA, ERP, DW, ETL, OLAP, DM, DSS, KMS, EIS) (see the glossary section)

Consequently, the proposed conceptual model provides the foundation for empirical investigation of the effect of three main categories of determinants consisting of; technological innovation, organizational, and environmental factors on adoption of BIDSA in Australian firms. Each of these factors below is discussed in the next section.

1. **Technological innovation factors**: 1) perceived benefit; 2) task complexity; and 3) system compatibility.
2. **Organizational factors:** 1) top management support; 2) organizational size (resources); 3) absorptive capacity; and 4) internal need.
3. **Environmental factors:** 1) competitive pressure; and 2) vendor selection

3.3 FACTORS IN THE ADOPTION BY ERP PERSPECTIVES

3.3.1 Technological Innovation Factors

The following technological innovation factors were included in this study: perceived benefits/barriers; complexity; and compatibility.

3.3.1.1 Perceived Benefits

Rogers (1983) found that relative advantage or perceived benefits had a positive relationship to the adoption of technology. Similarly, Kendall et al. (2001), Tan & Teo (2000), Thong (1999), and Moore & Benbasat (1991) found that relative advantage perceived benefits were the best predictor of the adoption of innovations. In an organisational adoption decision, perceptions of favourable benefits from an innovation provide economic and political legitimacy to the adoption decision (Clemons 1991). The degree of relative advantage is often expressed in terms of economic profitability, savings in time and effort, and cost reduction.

Initial research by Wixom & Watson (2001) indicates that BIDSA can offer several benefits to an organisation that include enabling effective decision support and business applications (e.g. CRM, SCM), facilitating data analytics, ensuring data integrity, accuracy, security, and availability; easing the setting and enforcing of standards, facilitating data sharing, and delivering the right information to the right person during the right time (Back 2002; Goodhue, Quillard & Rockart 1988; Goodhue, Wyboa & Kirsch 1992; Wixom & Watson 2001). This suggests that positive perception of benefits of IS organisations should provide an incentive for the ERP companies to develop the use of their BIDSA. Therefore, it is expected that BIDSA's perceived benefit is positively related to adoption of BIDSA.

3.3.1.2 Task Complexity

Complexity is defined as the degree to which an innovation is perceived as relatively difficult to understand and use (Rogers 1983). Complexity of an innovation can function as an inhibitor to adoption and further diffusion of the innovation as the organisation may not be able to integrate it with the rest of its procedures. The complexity of the technology (e.g. BIDSA) also creates greater uncertainty for successful implementation and therefore increases the risk of the adoption process. In addition, this could refer to the degree of professional knowledge the members of the organisation possessed. As noted, BIDSA has the potential to create radical changes to existing business processes and is often viewed within the context of business process reengineering (Wixom & Watson 2001). The lack of skill and knowledge would , in turn, generate difficulty when using the new technology, thereby affecting the organisation's adoption of innovative technology (Kwon & Zmud 1987; Premkumar, Ramamurthy & Nilankanta 1994). Thus, Rogers (1983) and Thong (1999) generalised that the complexity of an innovation is negatively related to its rate of adoption.

In contrast, some studies indicated that there is no relationship between complexity and innovation adoption (Kendall et al. 2001; Seyal & Rahman 2003; Tan & Teo 2000). From this, it could be implied that a few innovations are clearly understood by the adopter and are quickly accepted while others are not, and so will affect the rate of adoption (Nambisan & Wang 2000). Therefore, it is expected that BIDSA's complexity is negatively related to its adoption.

3.3.1.3 System Compatibility

Compatibility is defined as the degree to which an innovation is perceived in the consistent with the presently existing values, past experience, and needs of potential perception for adopters (Rogers 1983). In particular, compatibility refers to an innovation's compatibility with existing systems (in this case, retrained current systems), including hardware and software (Schultz & Slevin 1975). Bajaj (2000) indicated that this factor will cause changes in the organisation. Changes include: converting old data or information to be read by new architecture (e.g. BI architecture), retraining users to use, and the IS personnel to maintain software and hardware.

According to the BIDSA environment, it is likely that certain software will be retrained and must be integrated with the BI system. Several previous studies have shown that compatibility is associated with the adoption of innovations (Grover 1993; Moore & Benbasat 1991; Seyal & Rahman 2003; Thong 1999). Cooper & Zmud (1990) found that compatibility is an important predictor affecting the adoption of the use of material requirements planning (MRP) systems, which could be one application of decision support applications and BI systems. This implies that the adoption of BIDSA by ERP users is compatible with the specific business's objectives. Therefore, if the innovation is compatible with existing work practices, environments, and the firm's objectives, the firm will be more likely to adopt it. It is expected that the greater the perceived compatibility of the BIDSA with an organization's beliefs, values, and IT infrastructure, the more likely it will be adopted by the ERP user organizations.

3.3.2 Organisational Factors

The following organisational factors were included in this study: top management supports; organisational size; absorptive capacity; and internal need.

3.3.2.1 Top Management Supports

Top management support has been identified as a key predictor in the adoption and implementation of IT (Fink 1998). Several previous studies have shown that top management support is a significant predictor of technology adoption and leads to more successful IT use in many organisations (Caldeira & Ward 2002; Grover 1993; Kumar, Maheshwari & Kumar 2002; Seyal & Rahman 2003; Tan & Teo 2000; Thong 1999). It is important to create a supportive climate and adequate resources for the adoption of new technology (Premkumar & Roberts 1999).

Top management would be able to identify business opportunities for the exploitation of IT and their active involvement and support would provide appropriate strategic vision and direction for the adoption of new innovations (Thong & Yap 1995). Moreover, this characteristic would also send signals about the importance of the innovation and succeed in overcoming organisational resistance to accept the information system. As a result, securing the support of top management will lead to obtaining necessary assistance related to required capital spending and labour support, and the cooperation to complete for resources in the project-planning and development stage (Grover 1998). In addition, Wixom & Watson (2001) indicated that "top management" is as an important factor of BI success.

However, without the support from top management, it will result in stronger resistance from employees and will become a substantial barrier to the adoption of data warehouse (Haley 1997). Therefore, it is expected that the greater the extent of top management support, the more likely the organization will adopt BIDSA.

3.3.2.2 Organizational Size (Resources)

Some studies in organisational innovation adoption have indicated that there is no significant relationship between business size and organisational innovation adoption (Mistillis, Agnes & Presbury 2004; Sahadev & Islam 2005; Seyal & Rahman 2003). On the other hand, a number of previous studies have shown that business size has influenced the use of technology (Buonanno et al. 2005; Dholakia & Kshetri 2004; Rogers 1983; Thong 1999). Studies suggested that as the size of a business increases, so will the likelihood of information technology being present within the organisation (ABS 2000).

A study by Gibson & Arnott (2003) reported that business scale is as one of the factors that have an effect on the adoption of BIDSA in small businesses. It has been considered to be an adoption factor facilitator (Damanpour 1992) and has been used in IT adoption since researchers believe larger firms tends to have abundant resources, be more capable of bearing risks, and possess more power to urge trading partners to adopt IT (Zhu, Xu & Dedrick 2003). In order to adopting innovative IT, adequate resources could enhance this success (Poon & Wagner 2001; Tait & Vessey 1988). Organisational resources refer to the level of 1) financial and 2) technological resources that the firm has (Iacovou, Benbasat & Dexter 1995). Financial resources express an organisation's capital available for IT investments. This factor is considered because small and medium business organisation and budget setting tend to lack the resources that are necessary for information systems (Murphy et al. 2003; Paraskevas & Buhalis 2002). Moreover, the findings of Heung (2003) showed that financial resources and well-trained staff are important factors for some business sectors. BIDSA is an expensive, multiyear investment in terms of BI platforms, infrastructure, and applications.

IT sophistication (Paré & Raymont 1991) captures not only the level of technological expertise within the organisation, but also the level of management understanding of and support for using IT to achieve organisational objectives. To understand its value prior to adoption and later during implementation requires a diverse set of skills and expertise. Tan & Teo (2000) reported that technology infrastructure is the key determinant, which shifts to organisational capabilities in terms of integrating to leverage existing information systems and databases, and is significantly associated with organisational innovation adoption.

It suggests that larger firms usually have sufficient resources to compensate the accompanied limitations of huge expenses and labour required in the adoption of IS (Dewar & Dutton 1986; Levin, Levin & Meisel 1987). The degree of coordination of organisational resources is one of the most important factors in the adoption of a data warehouse (Grover 1998; Haley 1997; Wen, Chou & Yen 1997). Prior research by Barquin & Edelstein (1997), Haley (1997), and Watson & Haley (1997) indicated that the adoption of data warehouse technology comes with characteristics such as large expense and consuming much times). Thus, this study assumes that the coordination of organisational resources (funding, technology, time, etc.) is a key factor, which affects the adoption of BIDSA. Therefore, it is expected that organizational size is positively related to adoption of BIDSA.

3.3.2.3 Absorptive Capacity

Absorptive capacity is the ability of key organisational members to utilise available or pre-existing knowledge (Griffith, Redding & Reenen 2003). It facilitates a sort of reaction process of the knowledge with their mind (Alavi & Leidner 2001). This absorptive capacity of organisations indicates an ability to recognise the value of external and internal information, and to assimilate and apply it effectively to realise economic benefits. Sambamurthy & Zmud (1999) have suggested a need to be critical to organisations' innovativeness.

Applied to the IT area, organisations' absorptive capacity reflects the capacity to absorb information relating to appropriate IT innovations through employees' individual knowledge repositories, cognitive structures, and processes for supporting operational or strategic activities, and to enhance firm performance (Boynton, Zmud & Jacobs 1994). According to Nonaka (1991, 1994), research on new product development and management is supportive of the notion that supportive capacity is prerequisite for rapid innovation and flexible organisational response to changing market conditions.

Therefore, a major innovation like BIDSA requires an awareness of what it can provide or enable, and an understanding of how to exploit its potential within an organisational context. Rogers (1995) referred to this also as the embedded context (Tornatzky & Fleischer 1990). The adoption of BIDSA is unlikely unless key users can creatively identify unique ways through which new knowledge can be extracted by integrating data from multiple functional areas within the firm (Nambisan, Agarwal & Tanniru 1999). However, such creative thinking may be unlikely unless adequate knowledge exists within the firm. A study by Fichman (1992) noted that the ability to adopt is critical with respect to innovations; such ability has been found to be a key in adoption of open systems (Chau & Tam 1997). It is believed that organization absorptive capacity is a strong predictor of an organization's ability to adoption innovations (Cohen & Levinthal 1990). Thus, this study assumes that the absorptive capacity in the adoption stage is positively related to the adoption of BIDSA.

3.3.2.4 Internal Need

Previous studies (Premkumar & Ramamurthy 1995; Zmud 1984) showed that the internal need in an organisation is an important factor affecting the adoption of information technology. The adoption of BIDSA results from internal needs such as the demands for requiring better information from single data source faster (Watson & Haley 1997). Grover and Goslar's research (Grover & Golslar 1993) suggested that the internal needs can be classified as the needs for better response time, improving service quality, reducing costs, providing correct information, and raising competitive advantage. It would be beneficial to adopt BIDSA such as data warehouse technology only after organisational decision-makers completely understand the internal needs to necessitate such an adoption. Thus, this study assumes that internal needs in ERP companies will drive the decision for an adoption of BIDSA.

3.3.3 Environmental Factors

The following environmental factors were included in this study: competitive pressure; and selection of vendors.

3.3.3.1 Competitive Pressure

Competitiveness refers to the intensity of the level of competition in the environment within the industry where the firms operate (Lertwongsatien & Wongpinunwatana 2003). As mentioned by Porter & Miller (1985), to gain a competitive edge in their industries, firms need to differentiate themselves from competitors, positioning their products and services as premium goods. In highly competitive markets, innovation adoption would be necessary to maintain market position and share (Robertson & Gatignon 1986). Gatignon & Roberston (1989) have shown that higher levels of competition stimulate innovation adoption. The studies of Dholakia & Kshetri (2004); Lertwongsatien & Wongpinunwatana (2003); Levin, Levin & Meisel (1987), and Hannan & McDowell (1984) showed that a competitive environment was associated with the adoption of IT. It is believed that competition increases the likelihood of innovation adoption (Link & Bozeman 1991). Premkumar & Roberts (1999) found that competitive pressure was a significant factor in adopting new IT for small businesses. However, Thong (1999) could not find any support between the adoption decision or the extent of adoption and competitive pressures in his work on small business adoption of IS. Thus, it is assumed that the greater the competition, the more likely the ERP user organizations will adopt BIDSA.

3.3.3.2 Selection of vendors

Yap, Soh & Raman (1992), Thong, Yap & Raman (1996) and Wong & Lu (2005) found that vendors' support is an important factor for adoption/implementation of IS. Usually, the duties of a vendor include providing the software packages and hardware, training of users, and technical support. The importance of vendor support to a business attempting IS implementation has been highlighted by Senn & Gibson (1981). Thus, firms should carefully evaluate the possibility of outsourcing development of a BI based on their own surrounding situations. If the firms decide to use outsourcing to adopt BI, extra care should be taken in selecting the vendors (Kimball 1996). BIDSA is not only a software package, and the plans proposed by vendors may not be perfectly tailored for an enterprise. Thus, the enterprise cannot leave all the implementation plan and operating details in the control of vendors.

According to Powell (1993)'s study, the variable "selection of vendors" can be grouped and measured by quantifying the following items: the vendors' reputation and successful experience possessed; the capability with the technological competence of the system; the professional competence of the consultant. Moreover, information from consultants can be used as a supplement to provide ideas and assist organisations that lack the experience to adopt a new IT in their organisations (Haley 1997). It is expected that information consultants' assistance in the process affects the decision to adopt BIDSA. This study assumes that the selection of vendors affects positively the decision of adopting BIDSA.

3.4 RESEARCH QUESTIONS AND HYPOTHESES

Based on the literature review above, it can be concluded that there are several categories of factors: organisational, technological innovation, and environmental, which contribute to the adoption of BI and decision support applications. Consequently, the proposed conceptual model (see Figure 3-1) provides the foundation for empirical investigation of the following research questions in this study.

1. How do the company characteristics differ in the extent of adoption and implementation of BIDSA by Australian organizations?
2. What are the potential factors affecting the adoption of BIDSA in Australian business organisations? If there is a difference, in what kind of specific factors do the adoption and implementations of BIDSA differ from early adoption and non early adoption?
3. Which factors are the most important in the promoting/inhibiting of BIDSA?
4. Does this proposed model adequately describe previously successful adoption of BIDSA? And can it be used to predict future adoption of BIDSA in terms of particular factors?

In order to address these questions, the following hypotheses **(H)** were specifically examined in this study.

H1: "The stages of adoptions differ in the extent to which they use BIDSA in term of size of companies, industry types, and duration in using BIDSA"

H2: "Technology characteristics will be related to a decision to adopt BIDSA in Australian ERP user organizations".

> **H2a:** Perceived benefit will be a reflective indicator of technological constructs to BISDSA adoption.
>
> **H2b:** Task complexity will be reflective indicators of technological constructs to BISDSA adoption.
>
> **H2c:** System compatibility will be a reflective indicator of technological constructs to BISDSA adoption

H3: "Organisational factors will have an effect on the adoption of BIDSA in Australian ERP user organisations".

> **H3a:** Top management support will be a reflective indicator of organisational constructs to BISDSA adoption.
>
> **H3b:** Organisational size will be a reflective indicator of organisational constructs to BISDSA adoption.
>
> **H3c:** Absorptive capacity will be a reflective indicator of organisational constructs to BISDSA adoption.
>
> **H3d:** Internal need will be a reflective indicator of organisational constructs to BISDSA adoption.

H4: "Environmental factors will be related to a decision to adopt BIDSA in Australian ERP user organizations".

> **H4a:** Competitive pressure will be a reflective indicator of environmental constructs.

H4b: Vendor selection will be a reflective indicator of environmental constructs.

H5: "Organisational, technological, and environmental constructs are related to a decision to a successful adoption of BIDSA in Australian ERP user organizations".

3.5 SUMMARY

In summary, this chapter has described the importance and the success of the use of the BI and decision support technologies for the decision making environment. The purpose of this chapter was to propose a conceptual model for the adoption of BI and decision support applications by the Australian ERP user sector. The study related to the adoption of technological innovation in an organisation and ERP users. The findings of a comprehensive analysis of all factors affecting the use of BIDSA derived from extensive analysis of secondary sources, mainly existing adoption and diffusion literature and the literature on the diffusion of ICTs and decision support technologies in the ERP user sector, and complemented through exploratory study, were incorporated into the proposed model. The three important categories of factors: organisational, technological innovation, and environmental were combined into the proposed model to explain the facilitating and inhibiting factors for the use of BI and decision support applications.

The organisational factors consist of: 1) top management support; 2) organizational size; 3) absorptive capacity; and 4) internal need. Next, the technological innovation factors consist of: 1) perceived benefits; 2) task complexity; and 3) system compatibility. Last, the environmental factors for the organisational environment consist of: 1) competitive pressure; and 2) selection of vendors. The degree of adoption of the BIDSA will be measured in two levels in terms of early adopter and non-early adopter ERP users. Therefore, the proposed conceptual model provides the foundation for empirical investigation of the research questions (see section 3.3). Figure 3-2 below has summarized and demonstrated the conceptual model in this study.

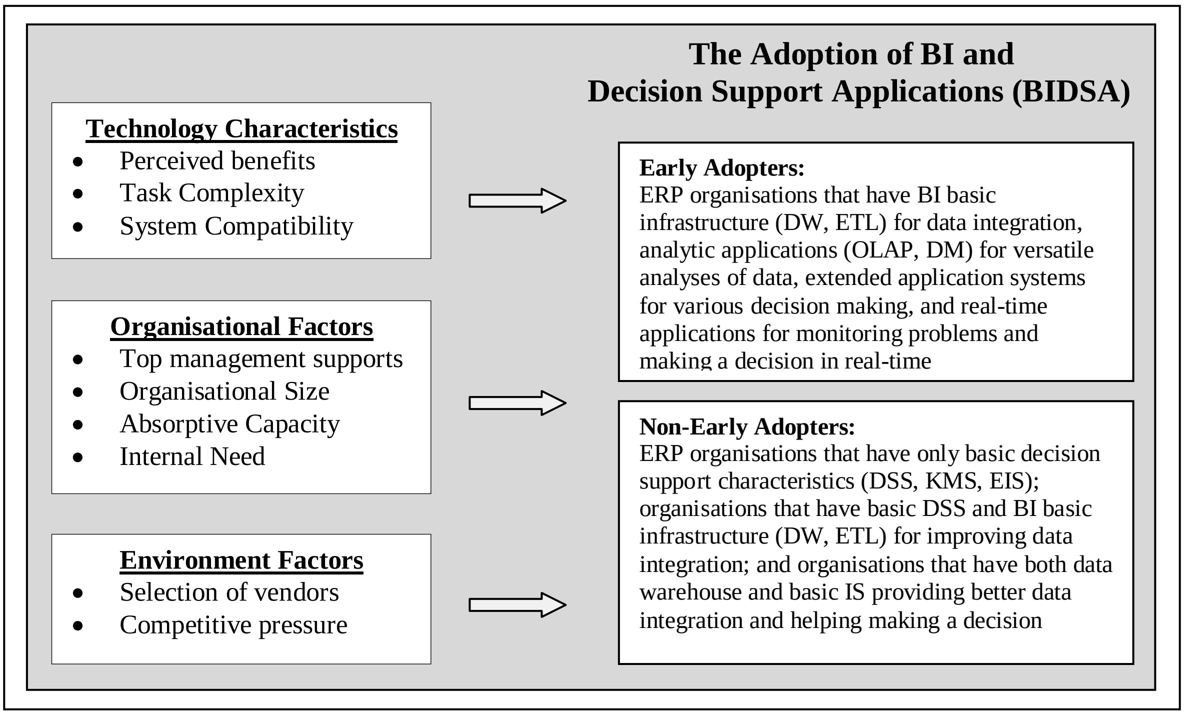


Figure 3-2: The conceptual model of adoption of BI and decision support applications (BIDSA)

Then, the next chapter will present the research methodology, as well as the research process to accomplish the research aims and answer the research questions.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 INTRODUCTION

In the previous chapter, the conceptual model and hypotheses of the study were discussed. In order to answer the research questions, Mingers (2001, p. 653; Tabachnick & Fidell 2001) defined research methodology as a structured set of guidelines or activities to assisting in generational valid and reliable research results. Thus, to measure the constructs and to empirically test the hypotheses derived from the research model, the purpose of this chapter is to describe the research methodology and design for examining the model of this study and to build theory that suggests an appropriate response to the research questions.

Types of research include exploratory, descriptive, quantitative, qualitative, and so on (Hussey & Hussey 1997). The methodology involved in this study starts with a preliminary study, followed by a quantitative approach which has been considered appropriate for the goal of the thesis. There were two stages in the research process: 1) a preliminary analysis of BIDSA systems by using short semi-structured interviews to provide introductory information; and 2) a questionnaire survey of senior ERP executives in Australia as the main part of the data gathering. The method of development of the research instruments, the measurement of validity and reliability of the research instruments, the methods of selection of the population and sample, data collection, and the data analysis techniques for this study are now described.

4.2 RESEARCH PROCESS

In formulating the research process for this research, a review of literature on innovation adoption factors was undertaken (see Chapter 2). To achieve this, Sekaran (2003) suggested that research conducted in accordance with the process based on the concepts of hypothetico-deductive method consists of eight steps.

- Observation (this was conducted but it was not used as a research method)
- Preliminary information acquiring data from semi-structured interviews in order to view what is happening and the reason for it happening. A researcher then gets an idea of the situation. That will assist in developing a questionnaire.
- Obtaining more and better information through a literature survey. This literature survey is conducted in order to acquire information so that the researcher can identify how issues have been tackled in other situations. Moreover, this step can provide information with additional insights into various possibilities and help to confirm that some variables might be good predictors of usage behaviour and behaviour intention (see Chapter 2).
- Theory formulation (theorising) is a stage in developing a theory incorporating all the relevant factors contributing to good predictors of usage behaviour and behaviour intention. The theoretical approach is used to integrate all the information in a logical manner, and is a collection of theories and models from literature in generating, conceptualising and testing the reasons for the problems. Thus, it explains the research questions or hypotheses, and clearly identifies and labels the variables (see Chapter 3).
- Generating various hypotheses for testing to examine whether the theory formulated was valid (see Chapter 3).

- Data collection: Questionnaires were developed based on various theorised factors, to determine the adoption and intention to adopt BIDSA (see Chapter 4).
- Data analysis: data obtained through the questionnaires was analysed to see what factors influence the adoption of BIDSA (see Chapter 5 and Chapter 6).
- Deduction is the process of arriving at conclusions by interpreting the meaning of the results of the data analysis (see Chapter 7).

Figure 4-1 below provides an overview of the processes and methods undertaken in this thesis to answer the research aims in Chapter 1, and to test the hypotheses proposed in Chapter 3. These steps are also summarised in the following figure, identifying the sections of this chapter relating to each step.

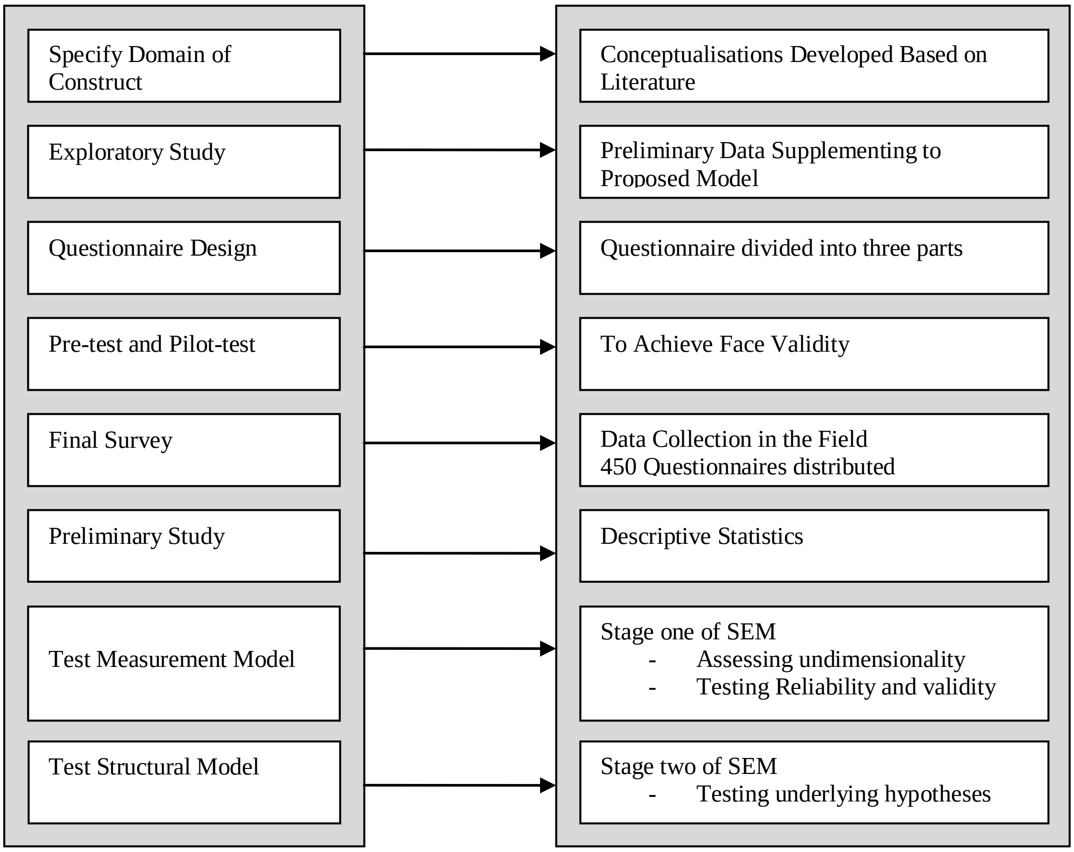


Figure 4-1: Overview of methodology in this research

4.3 RESEARCH METHODS

The research methodology and methods for this thesis were chosen in order to successfully achieve the research objectives. When considering the method that may be used in a research study, generally two research approaches are used in social science research studies including information systems (IS). These are quantitative and qualitative research methods. **Quantitative** methods involve numerical representation and manipulation of observations for the purpose of describing, explaining, and testing hypotheses (Creswell 2003). On the other hand, **qualitative** research involves non-numerical examination and interpretation of observations for the purpose of discovering the underlying meanings and patterns of relationships (Creswell 2003; Patton 2002). It emphasises the processes and meaning which are not rigorously examined or measured in term of quantity, amount, intensity or frequency. This can be conducted through in-depth interviews, focus groups, participant observations and case studies (Cavana, Delahaye & Sekaran 2001). However, results by using qualitative approach can vary from research to research, becoming problematic when researchers become fixated on exploratory research and do not progress beyond this to the hypothesis testing stage (Cherry 2000).

According to Neuman (2006), variables and relationships are the central idea in quantitative research and are useful in providing detailed planning prior to data collection and analysis and to providing tools for measuring concepts, planning design stages, and dealing with population or sampling issues. In addition, this approach utilises a deductive mode in testing the relationship between variables and to provide evidence for or against pre-specified hypotheses (Neuman 2006). As discussed in Chapter 2, innovation adoption literature indicates that there are relationships between adoption factors such as technological innovation factor, organizational factors, and environmental factors. This thesis attempts to investigate these relationships in Australian innovation context by testing the proposed hypotheses. Drawing on the existing literature of adoption of innovation technology including IS/IT/ICTs, this thesis developed a theoretical model to test the research questions (see Chapter 3), and the hypotheses (see Chapter 3). Punch (1998) maintained that the method used to conduct the research should be in line with the research questions. Thus, this thesis employs quantitative method to test hypotheses and then to answer the research questions.

4.3.1 Quantitative methods

As research methods are generally categorized into two types, quantitative and qualitative methods (Cherry 2000), Neuman (2006) described quantitative method as "*an organised method for combining deductive logic with precise empirical observations of individual behaviour in order to discover and confirm a set of probabilistic causal laws that can be used to predict general patterns of human activity*". Using a quantitative approach assists the researcher to establish statistical evidence on the strength of relationships between both exogenous and endogenous constructs (Amaratunga et al. 2002). Moreover, it is useful to acquire the statistical results for providing directions of relationships when combined with theory and literature.

Accordingly, as this approach involves statistical analysis and relies on numerical evidence to test hypotheses (Brunt 1997; Creswell 2003), this research focuses on the measurement and analysis of causal relationships between variables (Denzin & Lincoln 1994). In particular, it is grounded in a positivist social sciences paradigm that reflects the scientific method of the natural sciences (Gregor 2006). The positivist approach has its origins in a school of thought within the philosophy of science known as "logical positivism" (Babbie & Mouton 2001).

4.3.2 Research Paradigms

As research paradigms guide researchers to identify the relationship between variables to specify appropriate methods for conducting particular research (Guba & Lincoln 1994), the positivism paradigm has been considered the oldest and most popular philosophical approach in the physical and social sciences of other types of paradigms (e.g. post-positivism, critical theory, constructivism) (Easterby, Thorpe & Lowe 2002). According to Neuman (2006), positivist social science is used widely and the positivism paradigm forms the basis of natural science and has influenced scholars as a rational system.

Within this paradigm, researchers focus on facts and search for direct cause and effect, remaining external to the events being examined. This paradigm involves formulating hypotheses as a process of problem solving. These are subjected to empirical testing through a quantitative approach (Buttery & Buttery 1991). The quantitative approach provides objective, value free and unambiguous interpretation of reality (Guba & Lincoln 1994). In the line of this, information system research has been classified as positivist if there was evidence of formal propositions, quantifiable, measures of variances, hypothesis testing, and the drawing of inference about a phenomenon from the population sample (Orlikowski & Baroudi 1991).

Discussed by the underpinning of the positivism paradigm and based on the idea that research questions should interact with the methods used to conduct the research (Punch 1998), the thesis aims to measure underlying variables, as "*measurement of the variables in the theoretical framework is an integral part of research and an important aspect of quantitative research design*" (Cavana, Delahaye & Sekaran 2001, p. 186). In positivism the aim of research is explanation leading to prediction and finally control of the phenomena being researched (Guba & Lincoln 1994). From this point of view in this research, positivism applies quantitative method to test hypothetical deductive generalizations of the theory.

Although the quantitative approach has been criticized for its ability to produce theory and generate in-depth explanations of qualitative enquiry, it can verify the hypotheses and provide strong validity and reliability (Cavana, Delahaye & Sekaran 2001). Prior studies have applied this methodology which has been successfully used in similar studies (BuonannoFaverioPigni Ravarini 2005; Hwang et al. 2004; Lee, CP & Shim, JP 2007; Rai & Bajwa 1997; Ramamurthy, Sen & Sinha 2008; Thong 1999). Consequently, this methodology mainly was seen as suitability due to the objective of the research being to empirically investigate causal relationships among the underlying constructs.

On the above justification, this study is best classified as using a positivism paradigm and so the researcher decided to choose a quantitative rather than qualitative approach for this thesis.

4.4 RESEARCH DESIGN

As quantitative method was considered to be appropriate for this research, the research design involves a series of rational decision-making alternatives. According to Cavana, Delahaye & Sekaran (2001), measurement of variables in the theoretical framework is an essential part of research and a significant aspect of quantitative research design. Kerlinger (1986) suggested that research design works as "*a plan and structure of investigation so conceived as to obtain to research questions*". A plan is an overall scheme or program of the research. Although research designs are invented to enable to researcher to answer research question as validly, objectively, accurately, and economically as possible, research plans are deliberately and specifically conceived and executed to bring empirical evidence to bear on a research problem Kerlinger (1986). This research broadly addresses the question of why an organisation adopts or considers not adopting BIDSA.

As the aim of the thesis was to explore factors that affect the adoption of BIDSA in Australian ERP user sectors. The four research questions (see Chapter 3) used as the guide to accomplish the aim of this research are:

(1) How do the company characteristics differ in the extent of the adoption and implementation of BIDSA by organizations in Australia?

(2) What are the potential factors affecting the adoption of BIDSA by organisations in Australia? If there is a difference, in what kind of specific factors do the adoption and implementations of BIDSA differ from early adoption and non early adoption?

(3) Which factors are the most important in the promoting/inhibiting of BIDSA?

(4) Does this proposed model adequately describe previously successful adoption of BIDSA? And can it be used to predict future adoption of BIDSA?

Thus, the research process designed to achieve the aims and answer the questions was conducted in two stages: 1) the preliminary analysis of decision support technologies of BIDSA using short semi-structured interviews; and 2) the quantitative method using structured, closed item surveys.

4.4.1 The First Stage

This stage used a qualitative method involving an analysis of decision support applications. Because of the newness of the research area, it was first necessary to obtain preliminary data regarding the applications or specific features of decision support technologies relating BIDSA which are available in Australia.

The main objectives of the analysis of decision support applications were to:

- Evaluate the features and the extent to which information needs are met in decision support technologies in Australian firms.
- Start to deploy answers to research question one, and to provide support for the hypothesis.
- Possibly, supplement the results of the later questionnaire survey

The method for this stage (preliminary study) used semi-structured interviews to gather preliminary data for the research. Sekaran (2003) suggested that it is a useful data collection method to include at this stage. Thus, a qualitative method (short interviews) on the analysis of BIDSA could help in designing and developing a full questionnaire and perhaps assist to develop the theoretical model. These interviews were conducted at this stage to identify and evaluate features provided by BIDSA, as a source of preliminary data and to assist in answering the Research Questions One and Two.

There are seven major steps in the analysis of decision support applications. These steps are shown in Table 4-1 and will be discussed in later sections of the chapter.

The First Stage of the research Process (7 steps)			
Step 1	Literature review	See chapter 2	Section 2.6
Step 2	Instrument design	See chapter 4	Section 4.5.1
Step 3	Define term of BIDSA	See chapter 4	Section 4.5.2
Step 4	Define population size	See chapter 4	Section 4.5.2
Step 5	Define sampling techniques	See chapter 4	Section 4.5.2
Step 6	Data collection	See chapter 4	Section 4.5.3
Step 7	Data analysis	See chapter 4	Section 4.5.4

Table 4-1: Seven steps of the research process for the preliminary analysis of BIDSA

4.4.2 The Second Stage

For the second stage, quantitative research by applying a questionnaire survey method using structured, closed item questions was chosen as an appropriate method to acquire a profile of business firms in Australia in terms of whether they used or did not use BI and decision support applications (BIDSA). The main objectives of the questionnaire survey conducted were to:

- Identify the BIDSA adopted by Australian business firms
- Investigate the facilitating and inhibiting factors affecting the adoption of BIDSA by an ERP perspective in Australia; and
- Develop a model for successful adoption and diffusion of BIDSA by the ERP perspective in Australia

Thus, the quantitative questionnaire survey provided the main method to test the model and all the hypotheses (H1-H5), and to provide answers to Research Question One, Two, Three and Four as shown in Table 4-2.

Research Questions and Hypotheses	
Research Questions	**Hypotheses**
1) How do the company characteristics differ in the extent of adoption and implementation of BIDSA by Australian organizations?	**H1:** The stages of adoption differ in the extent to which they use BIDSA in terms of size of companies, industry types, and duration in using BIDSA
2) What are the potential factors affecting the adoption of BISDA by ERP users in Australia? If there is a difference, in what kind of specific factors do the adoption and implementation of BIDSA differ for early adopters and non early adopters. **3)** What kind of factors can be use to indicate the difference between early adoption and non-early adoption?	**H2:** Technology characteristics have an effect on the adoption of BIDSA in Australian ERP organisations. **H3:** Organisational factors are related to a decision to adopt BIDSA in Australian ERP organizations. **H4:** Environmental factors are related to a decision to adopt BIDSA by ERP organizations in Australia
4) Does this proposed model adequately describe previously successful adoption of BIDSA? And can it be uses to predict future adoption of BIDSA in term of particular factors	**H5:** Organisational, technological, and environmental constructs are related to a decision to a successful adoption of BIDSA

Table 4-2: Research questions and hypotheses

There were eight major steps in the research process for the quantitative questionnaire survey. These are shown in Table 4-3 below and will be discussed in later sections of this chapter.

The Second Stage of the Research Process (8 steps)			
Step 1	Define questionnaire survey	See chapter 4	Section 4.6.1
Step 2	Short semi-structured interviews from stage one (preliminary study)	See chapter 4	Section 4.6.2
Step 3	Instrument design	See chapter 4	Section 4.6.2.1, 4.6.2.2, and 4.6.2.3
Step 4	Pre-test and pilot-test	See chapter 4	Section 4.6.2.4 and 4.6.2.5
Step 5	Define population size	See chapter 4	Section 4.6.3
Step 6	Define Sampling techniques	See chapter 4	Section 4.6.3
Step 7	Data collection	See chapter 4	Section 4.6.4
Step 8	Data analysis	See chapter 4	Section 4.6.6

Table 4-3: Eight steps of the research process of the stages of the quantitative questionnaire survey

Consequently, in order to summarise, the research process was divided into two stages: 1) a exploratory study (as preliminary study) to analyse decision support applications utilising a short interview instrument to consider decision support applications in Australia; and 2) a quantitative method using self-completing, closed item questionnaires to investigate the factors affecting the adoption of BIDSA in business organisations in Australia. Details of each stage of the research process are provided in the following sections.

4.5 THE PRELIMINARY STUDY FOR ANALYSIS OF DECISION SUPPORT APPLICATIONS

An analysis of decision support applications was undertaken as the first stage of this study to have a better understanding of the decision support components relating to the use of BIDSA in Australia. However, it was expected that preliminary information gathering (by interviews) could help in designing a full survey questionnaire and perhaps assist to develop the theoretical framework. Short semi-structured interviews were selected and this preliminary study provided a useful data (Sekaran 2003). This method is useful in that the interviewer can adapt the questions as necessary, clarify doubts, and ensured that the responses are appropriately understood by repeating the question, and could establish relationships and motivate respondents. Moreover, rich data could be obtained. Key variables from the literature review were elaborately combined with information from interviewing with the aim of developing an effective questionnaire used in this survey.

Therefore, in order to perform the initial exploratory study, during the month of August 2007 in the conference of the SAP Australian User Group (SAUG) summit 2007, short semi-structured interviews were conducted by approaching twenty ERP (SAP) managers. Each interview took approximately ten to fifteen minutes to complete. The researcher had two instruments and a list of pre-determined open-ended questions but could ask other relevant questions. This section has four parts: 1) instruments for the analysis of decision support technologies; 2) sampling of organisations using decision support technologies; 3) data collection; and 4) data analysis.

4.5.1 Instruments for Analysis of Decision Support Applications

For this study, the researcher worked on the sample decision support technology instruments and determined open-ended questions based on the literature review to evaluate the features of decision support applications and decision maker's procedure needs by using short semi-structured interviews in Australia.

- The first instrument is lists of decision support technologies used for this study. This was based upon the works of Gibson & Arnott (2003), McDonald (2004), Foster, Hawking & Stein (2005), and Hawking, Foster & Stein (2008). The modified decision support technology samplings grouped fourteen attributes into 5 main categories: 1) Basic BIDSA; 2) BIDSA infrastructure; 3) BIDSA analytic applications; 4) BIDSA extended business applications; and 5) BIDSA real-time applications. The first instrument is provided in Appendix (A4).

- The second instrument is lists of factors aimed to investigate the extent to which ERP users are concerned with factors affecting the adoption of BIDSA. Fifty eight attributes relating to factors affecting BIDSA adoption are based on (e.g. Rogers (1983, 1995), Tornatzky & Fleischer (1990), Premkumar & Ramamurthy (1995), Grover (1993), Chau & Tam (1997), Damanpour (1991), Thong (1999), and Hwang et al. (2004)) categorised into four contexts: 1) decision maker characteristics; 2) system (technology) characteristics; 3) organisational characteristics; and 4) environmental characteristics were used to be as a checklist option and guidelines while doing an interview. The second instrument of potential factors is provided in Appendix (A5).

- Predetermined open-ended questions aimed to investigate the environment (e.g. idea, reason, experience) relating to technology, user, and organisation associated with the use of BIDSA from IT executives. These will be used to identify why the participants answered each question as they did.

4.5.2 Sampling

For standardisation, the criteria applied for the selection of the population and the sample is presented below.

4.5.2.1 Population size

The population for this study was chosen by applying these criteria.

- **Criterion 1**: ERP users for this research had already adopted BIDSA.
- **Criterion 2**: Identified using the definition of ERP users which can be defined as members of SAP user groups. Most of them in this stage are from the SAP Australian Group (SAUG) in Australia.

ERP falls into the category of packaged software applications with the added feature of integration and these applications are available from vendors (e.g. SAP, Oracle), which are recognised currently as the top ERP vendors (Reilly 2005). As a member of this group, SAP is a suitably high-dynamic system that can integrate decision support applications (e.g. SAP R/3) for enterprises. The SAP users have the market leading ERP system and in order to increase understanding of how BI systems may affect the adoption of business organisations. This group is appropriate to investigate because ERP adoption and implementation continues to grow globally (Markus, Tanis & Fenema 2000). It was shown that SAP has approximately 56 % of the ERP market worldwide and 75 % of the Australian market (Foster, Hawking & Stein 2005). The lists of the SAP Australian user group were chosen because they included a large number of ERP user members that were among the largest organisations for providing a list of ERP user sectors in Australia.

4.5.2.2 Sample Selection

The procedure of selecting ERP managers to be face-to-face interviewed was based on simple convenience sampling as follows. For convenience, twenty SAP managers were selected from different industries (e.g. manufacturing, servicing, and public sectors) from over hundreds of attendants of the SAP Australian Group Summit 2007 in Sydney. In this case, there was no bias limitation because all SAP attendants were from different parts of Australia and from various industries, and the respondents were informed that the information they provided would be kept strictly confidential.

4.5.3 Data Collection

Each ERP user participant, based on simple convenience sampling, was assessed by two instruments as mentioned above for the presence or otherwise of the aforementioned seventeen attributes of decision support features and twenty nine attributes of potential factors affecting the adoption of BIDSA provided by ERP users. The researcher coded “X” with specific features in the sheet that participants answered. Insight details relating to the BIDSA environment provided by ERP managers were investigated and categorised.

4.5.4 Data Analysis

Data analyses were conducted and described by putting them into a specific table (see Appendix A2). Results of the exploratory study were described and are showed in the tables in Appendix A2, Table A2-1 and Table A2-2. Descriptive statistics test was used with appropriate consideration relating to the nature of the data (Pallant 2005). Descriptive statistics including frequency and percentages were used to quantify the presence or otherwise of the attributes as mentioned by the two instruments and open-ended question option.

4.6 QUANTITATIVE APPROACH USING SURVEY METHOD

According to Cavana, Delahaye & Sekaran (2001), measurement of the variables in the theoretical framework is an essential part of research and a significant aspect of quantitative research design. Moreover, this study used a deductive and positivist approach for testing the conceptual model. As it utilized survey research methodology, which is a positivistic methodology, this was found appropriate to achieve the objectives of this study.

Yin (1994) suggested two main reasons for using survey technique, which other techniques cannot provide. For example, a number of the research questions in this study are related to 'who', 'what', 'when', 'where', 'how many or how much', and 'to what extent'. These are appropriate for surveys, while the question type using 'how' and 'why' are suitable for a case study (Yin 1994). The nature of questions in this research being investigated, for instance 'what are the innovation factors that influence the BIDSA adoption by ERP user organizations in Australia?' or 'how many fulltime employees are currently working in your company?' are appropriate for the use of a survey-based research approach. Another support is the degree of focus upon contemporary events. The survey method is selected in examining contemporary events as opposed to historical events (Yin 1994). This study emphasizes the ongoing contemporary issues of diffusion of ICTs (e.g. BIDSA), and employee attitudes (e.g. factors in adopting new ICTs).

According to Newsted, Huff & Munro (1998), survey research is one of the most popular methods used by information systems researchers. This method is the systematic gathering of information from respondents for the purpose of understanding and/or predicting some aspect of the behaviour of the population of interest (Tull & Hawkins 1990). In other words, survey research can be described as a mode of inquiry that involves the collection and organisation of systematic data and the statistical analysis of the results (De Vaus 1986; Marsh 1982). In survey research:

- A large number of respondents are chosen to represent the population of interest;
- Systematic questionnaire or interview procedures are used to elicit information from respondents in a reliable and unbiased manner; and
- Sophisticated statistical techniques are applied to analyse the data (Singleton, R et al. 1988)

As discussed in Chapter 1, the proposed theoretical model was evaluated using a sample group of ERP user organizations in Australia. For this purpose, self administered survey methodology was found to be the most appropriate tool in collecting the data. A closed item self administered questionnaire was utilised as the main method in order to test the model and hypotheses as well as to answer the research questions. In addition, self-administered questionnaires present a challenge in which they rely on the clarity of the written word more than on the skill of interviewers (Zikmund 2003). However, this method has a number of advantages as: 1) it is designed to deal directly with the nature of respondents' thoughts, opinions, and feelings and collect information on belief, attitudes, and motives (Burns 2000; Shaughnessy & Zechmeister 1997); 2) it is an effective tool, especially when the investigator does not require, or has little control over behaviour events (Yin 1994); 3) it provides an accurate means of assessing information about the sample and enables the researcher to draw conclusions about generalising the findings from a sample responses to a populations (Hair et al. 2006); 4) it is more concerned about causal research situations (Hair et al. 2006); and 5) it is quick, inexpensive, efficient, and can be administered to a large sample (Zikmund 2003).

This section consists of six parts: 1) the method of the questionnaire survey; 2) development of the survey questionnaire; 3) population and sampling; 4) data collection; 5) validity and reliability of the survey questionnaire; and 6) data analysis.

4.6.1 The Method of the Questionnaire Survey

Questionnaire surveys have been commonly used in recent studies regarding the use of IS/IT/ICTs and decision support technologies (e.g. Hwang et al. (2004), Buonanno et al. (2005), Xu & Quaddus (2005), Ikart & SDitsa (2004)), and also widely used in the previous studies on organisational technological innovation adoption (e.g. Chau & Tam (1997), Thong (1999), Chen (2003), Chen & Williams (1998). This is because questionnaire surveys enable researchers to acquire data fairly easily, and the questionnaire responses are easily coded (Sekaran 2003).

Questionnaires can be personally administered or by mail. By assessing the advantages and disadvantages of the method proper for the questionnaire survey, self completion questionnaires by mail were considered the most straightforward method of collecting data as well as being the quickest and most cost effective. Moreover, the mailing technique can cover a wide geographical area. As many ERP user organizations are scattered in the eight regions in Australia, this technique can provide low expense and time consumption. Thus, it is efficient to use survey questionnaires by mailing to cover all states where the companies are located.

Sekaran (2003) suggested that the advantage of the questionnaire method is that administrating questionnaires to large numbers of individuals simultaneously is less expensive and less time consuming than interviewing. Furthermore, the participants can complete the questionnaires of their convenience (Sekaran 2003; Zikmund 2003). However, there might be a number of problems associated with the use of questionnaires relating to the issue of confidentiality (Hussey & Hussey 1997). With this concern, the covering letter to all participants noted that the data collected would be strictly handled in consideration of issues of anonymity and confidentiality. Nevertheless, any doubts while doing questionnaires by respondents is another drawback because their concerns cannot be clarified (Sekaran 2003). Particularly, the respondents of this study were high level IT managers who were very busy and had limited free time.

It is expected that the return rate of mail questionnaires will typically be low, and with a very low return rate it is hard to generate the representativeness of the sample. A 30 percent response rate is considered acceptable (Sekaran 2003). With this disadvantage, the researcher therefore utilised much effort in order to improve the response rate by providing an envelope addressed to a particular participant to thus ensure successful delivery.

4.6.2 Development of Survey Questionnaire

An extensive search of the literature in the area of the information systems, business intelligence and decision support applications (BIDSA), and innovation adoption by organisations revealed that there has been very limited research in the decision support field. No existing questionnaires were found to be directly applicable, specifically addressing all issues relating to business intelligence, innovation and diffusion by the ERP user, focused in this study.

As previously mentioned in August 2007, short semi-structured interviews (preliminary study) were conducted by twenty SAP managers at the SAP Australian user group (SAUG) summit 2007 in Sydney, Australia. The participants were senior managers or similar level and were selected because they could be one of the team of decision makers relating to the decision support technologies in ERP users. The interview questions were designed to investigate:

- General information about the company's profile;
- The key reasons for, and problems influencing, the adoption of BIDSA by business organisations;
- The benefits and costs of BIDSA adoption;
- Factors in Australia that support the use of BIDSA.

Therefore, the results of these interviews (e.g. opinion, suggestions, example, and experiences) provided direction as to what factors were essential for the adoption of BIDSA by the organisation, and what could be elaborated on the design of the main questionnaires. The results of the semi-structured interviews (preliminary study) are included in Appendix (A2).

4.6.2.1 Development of Questionnaire Items

For this study, to draw up appropriate questions for questionnaires, key variables from the literature review on innovation adoption in organisations were combined with variables identified from the results of the exploratory study by short interviews. Variables that were utilised to formulate the questions for final questionnaires are listed in Table 4-4 below. From Table 4-4, variables used in the identification of factors affecting the adoption of BIDSA by ERP user organizations consisted of "independent" and "dependent" variables.

Operationalisation of Variables	
Variables	**Definitions**
Independent Variables	
1. Organisational Factors	
1.1 Top Management Support	The level of influence of CEO/CIO support on IS effectiveness (Grover 1993)
1.2 Organisational Size/ Resources	The level of financial and technological resources of the firm and availability of technology support (Iacovou, Benbasat & Dexter 1995)
1.3 Absorptive Capacity	The level of ability to recognise the value of external and internal information to realize economic benefits (Cohen & Levinthal 1990)
1.4 Internal need	The ability to completely understand the internal needs to necessitate use of BIDSA (Grover & Golslar 1993)
2. Technological Innovation Factors	
2.1 Perceived Benefits	The level of recognition of the relative advantage that innovation can provide the organisation (Rogers 1995)
2.2 Compatibility	The degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters (Rogers 1995)
2.3 Complexity	The degree to which an innovation is perceived as relatively difficult to understand and use (Rogers 1995)
3. Environmental Factors	
3.1 Selection of Vendors	The level of characteristics required of vendors for outsourcing (Powell 1993)
3.2 Competitive Pressure	The level of BIDSA capability of the firm's industry, and most importantly to that of its competitors (Hwang et al. 2004)
Dependent Variable	
Adoption of Business Intelligence and Decision Support Applications (BIDSA)	Early adopter and non-early adopter ERP user sectors (Foster, Hawking & Stein 2005; Gibson & Arnott 2003; Hawking, Foster & Stein 2008; Rogers 1995)

Table 4-4: Operationalisation of variables in the research

The dependent variable in this context is the adoption of BIDSA by ERP user organizations and is defined in terms of business intelligence and decision support applications (BIDSA) used to support better decision making of ERP user organizations. The dependent variable was measured in terms of early adopter and non-early adopter organisations.

- Early adopter ERP users have: 1) data warehousing for data acquisition and storing (e.g. data warehouse, ETL, data mart); 2) analytic application for versatile analyses of data (e.g. OLAP, data mining); 3) extended application system for various business decision-making (e.g. CRM, SCM); and 4) BI real-time applications for making decision in real-time.

- Non-early adopter ERP users include: 1) firms that have no information analytic applications; 2) have only basic IS for decision support (e.g. DSS, EIS, KMS); and firms that have only data warehouse for data integration.

The independent variables in this study were categorised into three groups of factors:

- Organisational factors (top management support, organisational size/resources, absorptive capacity, and internal need)
- Technological innovation factors (perceived benefits, task complexity, and system compatibility)
- Environmental factors (competitive intensity and selection of vendors)

4.6.2.2 Scoring Method

Almost all of the questions in the questionnaire were designed in a closed form. Dichotomous scales and categorical scales were used for the questions regarding ERP user types in the first section of the questionnaire. In the second part, regarding questions about factors affecting the adoption of BIDSA, a Likert rating scale was used. This scale is appropriate for measuring attitudes, beliefs or feelings (Singleton & Straits 1999). Moreover, for data obtained using an interval scale, parametric statistical analysis may be used (Hair et al. 2006; Zikmund 2003). Therefore, a Likert scale was selected for its ability to measure attitudes or beliefs.

For most of the questions in the second section respondents were asked to rate the extent of their agreement or disagreement with the statements on a seven-point Likert rating scale, ranging from 1 = strongly disagree, 2 = disagree, 3 = slightly disagree, 4 = neither disagree nor agree, 5 = slightly agree, 6 = agree, and 7 = strongly agree. This seven-point scale was selected as scales with more response categories have been found to be more reliable and valid than shorter scales (Singleton, RA & Straits 1999).

4.6.2.3 Questionnaire Design

Sekaran (2003) indicates that the research should focus on three areas when designing questionnaires: 1) wording of the questions; 2) planning of issues of how the variables will be categorised, scaled, and coded; and 3) the general appearance of the questionnaire. For this research the aim in designing the questionnaire was to consider the basic criteria of relevance and accuracy (Zikmund 2003).

Thus, the questionnaire (see Appendix A3) consisted of sixty two questions within three parts. The details of each part are as follows:

- Part I (Question1-11) was designed to gather background information about the respondents
- Part II and Part III (Part II: Question 1-44; Part III: Question 1-7) was designed to examine the factors affecting the adoption of business intelligence and decision support applications (BIDSA) by ERP user organisations. The questions of Part II contain independent variables, while PART III represents the questions indicating dependent variables for data collection. These questions were developed and divided among three main concepts of organisational, technological innovation, and environmental characteristics.

Variables and corresponding questions in the questionnaire for each concept according to the conceptual model are summarised in Table 4-5 below.

Questions in the "Adoption of BIDSA" Questionnaire			
Variables	**Items**	**Question (s)**	
		Part II	**Part III**
Organisational Factors			
Perceived Benefits	4	1-4	
Complexity	5	5-9	
Compatibility	5	10-14	
Technological Innovation Factors			
Top Management Support	5	15-19	
Organisational Size	5	20-24	
Absorptive Capacity	5	25-29	
Internal Need	5	30-34	
Environmental Factors			
Business Competition	5	35-39	
Selection of Vendors	5	40-44	
Adoption of BIDSA	5		2-6

Table 4-5: Questions in the "Adoption of BIDSA" questionnaire

4.6.2.4 Pre-testing Questionnaire

Hunt, Sparkman & Wilcox (1982, p. 270) pointed out that the researcher needs to ask "*Will the instrument provide data of sufficient quality and quantity to satisfy the objectives of the researchers?*" Moreover, the benefits of a pre-test prior to conducting the main survey have been supported by many researchers (Churchill 1995; Hunt, Sparkman & Wilcox 1982; Zikmund 2003). Pre-testing is defined as "a trial run with a group of respondents used to screen out problems in the instructions or design of a questionnaire" (Zikmund 2003).

Therefore, before final administration of the questionnaire, every question in the questionnaire was thoroughly evaluated by means of a pre-test. The purpose of the pre-test was to evaluate how each question was understood and to check the range of variation in the responses (De Vaus 2002). Sekaran (2003) suggested that it is important to pre-test the questionnaire used in the survey to ensure that the respondents understood the questions posed so there is no ambiguity and no problems associated with wording or measurement. In addition, Zikmund (2003) suggested that the size of the pre-testing group may be 25 or 50 subjects.

For this study, there were two steps of pre-testing.

- First, 25 graduate students of Victoria University were willing to participate in the pre-testing stage and so the questionnaires were pre-tested with research professionals, who are Ph.D. candidates specialising in the information systems and management fields. Additionally, IS graduate students taking an IS Project Management class (semester 1, 2008) were selected to also do so. Both researchers and IT professionals at Victoria University thus assisted to identify any difficulties with question wording, including effective use of language and clarity of content, formatting, instructions, and timing to complete the questionnaire.
- Second, all comments and recommendations obtained were used to correct and edit the questionnaire before going to the stage of a pilot study. Further to the empirical results, respondents' answers identified that there was a need for addition modifications. For example, the definitions relating to this innovation are very important for the understanding of doing the survey. In addition, appropriately logical questions were reorganised by applying the result of pre-testing. Overall, after the above pre-test procedures, minor changes to statement wording and layout were made to the instrument to ensure that the questions were readily understood by all respondents (Zikmund 2003). As no major modifications were made to the instruments, a further pre-test was not considered.

4.6.2.5 Pilot Survey Questionnaire

A pilot study was done by selecting a large organization with IT managers who could be declared as members of the ERP user groups and who had made a decision regarding the adoption of decision support applications. These participants were selected because they were in the best possible position to provide answers about their views in their organisations. This pilot study was conducted to detect weaknesses in design and instrumentation and to provide proxy data for selection. According to Ticehurst & Veal (2000) the purpose of pilot surveys is to: 1) test questionnaire wording; 2) test question sequencing; 3) test questionnaire layout; 4) gain familiarity with respondents; 5 estimate response rate; 5) estimate completing time; and 6) test analysis procedures. In addition, the size of the pilot group may range from 25 to 100 subjects (Cooper & Schindler 2006).

In this study, 100 questionnaires were sent to the firms of prospective ERP managers (from SAUG) in among the manufacturing, servicing, and public sectors. Replies from 27 respondents who are IT managers were received. However, 25 questionnaires were completely useful and suitable for doing pilot study (Cooper & Schindler 2006). Based on the feedback from respondents and results of data analysis (e.g. reliability test, validity test, and some basic data analysis), modifications were made to the questionnaire design such as the format of the questionnaire in order to improve understanding for the questionnaire survey stage of the study. The internal consistency reliability based on Cronbach's Alpha for measurement items was employed. It was clear that the pilot study survey could be used to test out all aspects of the survey and not just question wording (Ticehurst & Veal 2000). A copy of the final survey instrument used for this thesis is provided in Appendix (A3).

As Shown in Table 4-6 below, the values for the Cronbach Alpha coefficients ranged from 0.752 to 0.846, and were positively acceptable for this study (Sekaran 2003), based on rules of thumb about the size of Cronbach's alpha coefficient (Hair et al. 2006) (see rationale in Table 4-8).

Reliability Results of the Pilot Survey						
Measurement Items	**Items**	**Cronbach's Alpha**	**Reliability Results**	**Inter-Item Correlation**	**Item-Total Correlation**	**Remarks**
Technological Innovation Factors						
Perceived Benefits	4	0.805	**Good**	0.461-0.678	0.582-0.746	
Complexity	5	0.817	**Good**	0.527-0.682	0.622-0.733	
Compatibility	5	0.803	**Good**	0.428-0.784	0.519-0.697	
Organisational Factors						
Top Management Support	5	0.845	**Good**	0.565-0.737	0.650-0.782	
Organisational Readiness	5	0.738	**Acceptable**	0.468-0.661	0.549-0.659	
Absorptive Capacity	5	0.752	**Acceptable**	0.487-0.628	0.586-0.693	
Internal Need	5	0.801	**Good**	0.442-0.697	0.565-0.759	
Environmental Factors						
Business Competition	5	0.846	**Good**	0.624-0.690	0.680-0.731	
Selection of Vendors	5	0.814	**Good**	0.508-0.757	0.554-0.603	

Table 4-6: Reliability results of the pilot survey

Most of these are considered to be good and very good (greater than 8.0) (see rationale in Table 4-8), only two are acceptable (in 0.7 range) as shown in Table 4-6. This indicates that items in each set (concept) are positively correlated to one another. Thus, items in each set are independent measures of the same concepts, and also indicate accuracy in measurement.

However, another measure to assess internal consistency measure is the inter-item-total correlation (the correlation of the items to the summated scale and the inter-item correlation) (Hair et al. 2006). According to Robinson, Shaver & Wrightsman (1991), it has been suggested that the item-to-total correlations should exceed 0.5 and the inter-item correlations should exceed 0.3. For the pilot study examination, all item-to-total correlation values exceed 0.5and most of the inter-item correlation values exceed 0.3. These values suggested that the questionnaire survey was a reliable measurement tool.

As shown in Table 4-6, it was found that the reliability with coefficient alpha and correlation values of the questionnaire of the pilot study were acceptable. However, some minor changes were made to the questionnaire (e.g. wording) after implementing the pilot study. The instrument was developed based on the theoretical literature survey as well as with content validity with expert agreements. Therefore, the measures of the instrument provided adequate coverage of the concepts. It was also shown that the instrument was reliable and valid when considering content validity and construct validity using correlation analysis (Hair et al. 2006) and was ready to be distributed as the main survey.

4.6.3 Population and Sampling

The population of this research, the entire group of people that the researcher wishes to investigate (Sekaran 2003), was IT executive professionals within the ERP users who already had experience in adopting and using decision support technologies in Australia. As mentioned in section 4.5.2.1, ERP user organizations selected for this study were identified utilising the definition of this sector from the SAP Australian customers.

There was a total sampling of approximately 150 ERP user organisations in Australia (SAP customers) (Bennett 2002 cited in Stein, Hawking & Foster 2003). The total sample was collected from the conference of SAUG Summit 2007and recent reports of Australia’s largest enterprises (BRW 2006, 2007). This study surveyed the total sample of 150 ERP user organizations in Australia, thereby generating data that were not only accurate but also precise (Zikmund 2003, pp. 369-70).

Sekaran (2003) suggested that sampling design and the sample size are important to establish the representativeness of the sample for generalisability. A sample is a subset of the population which comprises some members selected from the population. However, Roscoe (1975) proposed that following rules of thumb for determining sample size:

- Sample sizes larger than 30 and less than 500 are appropriate for most research
- When samples are to be divided into sub-samples, a minimum sample size of 30 for each category is essential
- In multivariate research, the sample size should be several times as large as the number of variables in the study

With respect to the physical size of the samples, statistical theory does provide some tools which indicate the minimum sample size needed for various statistical techniques used in data analysis presenting in the Table 4.7 below.

The Statistical Analysis Techniques	
Analysis Techniques	**Sample Sizes**
Structural Equation Modelling (SEM)	100-150 (Hair et al. 2006)
When comparing between major groups	20-50 in each group (Aaker & Day 2002)

Table 4-7: The statistical analysis techniques used in this study and their minimum sample size required

4.6.4 Data Collection

This survey research was conducted in eight regions of Australia. The questionnaire was addressed to 450 particular management individuals. The questionnaire survey was conducted from May to August 2008. A package was mailed directly to each of 450 senior IT managers of ERP user organizations in Australia. The package contained three items: a covering letter (see Appendix A6); a questionnaire; and a prepaid reply envelope. In order to ensure participants clearly understood about the objectives of this survey, the covering letter explained the purpose of the survey and requested the managers to return the completed questionnaire within three weeks in the prepaid reply envelope. The researcher was however concerned about the response rate for this survey. In order to increase the response rate, a follow-up procedure was also employed in this study that involved a second mailing of questionnaires to those participants that had not responded within three weeks.

4.6.5 Validity and Reliability of the Survey Questionnaire

Testing goodness of data by testing the reliability and validity of measures can be used to ensure the quality of findings and conclusions. Reliability and validity are separate but closely related concepts (Bollen 1989). Thus, to ensure the precise and accurate instruments developed for this study, it was necessary to have procedures for "testing goodness" of data for measurement. There are two criteria for testing the goodness of measures: validity and reliability (Sekaran 2003).

4.6.5.1 Validity

According to Ticehurst & Veal (2000), business research encounters difficulties about validity, particularly in the measurement of attitudes and behaviour since there are often doubts about the true meanings of responses made in surveys, interviews, and the self-reporting of behaviour. Therefore, it is necessary to validate the constructs of this study. Validity is the extent to which the data collected truly reflect the phenomenon being studied. According to Zikmund (2003), validity means "the ability of a scale to measure what was intended to be measured". Punch (1998) pointed out that validity represents the relationship between the construct and its indicators. Three points relating to aspects of valid constructs were suggested by Nunnally & Bernstien (1994). First, the construct should be seen as a good representation of the domain observable related to the construct. Then, the construct should represent the alternative measures. Last, the construct should be related to other constructs of interest. Sekaran (2003) suggested that several types of validity tests for testing the goodness of measures include content validity, criterion-related validity, and construct validity. However, in this study, content validity and construct validity, used by many researchers, were chosen to establish the validity of the survey questionnaire (Thong 1999; Thong & Yap 1995).

4.6.5.1.1 Content Validity

Content validity or face validity is the first type used within this thesis. It is a method to evaluate the validity of an instrument by the judgement of a group of experts in order to ensure that the questionnaire has an adequate and representative group of questions that reflect the real meaning of the concept (Cavana, Delahaye & Sekaran 2001; Zikmund 2003). This assesses the correspondence between the individual items and the concept through ratings by expert judges, and pre-tests with multiple sub-populations or other means (Hair et al. 2006).

In this study, the content validity of the survey questionnaire was considered because it was tested by means of a pre-test approach using research professionals and IT managers in the ERP user organisation as described earlier. In addition, development of the questionnaire of this study was based on the results of the short interview (exploratory study) and the findings from the relevant literature review on innovation adoption. Cavana, Delahaye & Sekaran (2001) suggested that content validity can be achieved from doing literature and conducting qualitative research. It was ensured that the survey questionnaire would provide data relating to accepted meanings of the concepts involved. Thus, content validity was achieved by generating the items from the conceptual background and through obtaining experts' opinions of the items.

4.6.5.1.2 Construct Validity

Construct validity is another type used for an assessment of the questionnaire's capability to record data that accurately reflects the theory upon which the questionnaire is based on Sekaran (2003). In other words, construct validity testified that the instrument did tap the concept as theorised. Thus, this measure of validity refers to developing correct and adequate operational measures for the concept being tested (Yin 1994). Sekaran (2003) suggested that convergent validity examines whether the measures of the same construct are correlated highly, otherwise discriminant validity determines that the measures of a construct have not correlated too highly with other constructs. Most researchers test the construct validity by means of convergent and discriminant (Campbell & Fiske 1959; Peter 1981). Thus, construct validity is established in this thesis by analysing convergent validity and discriminant validity.

Various methods have been recommended for assessing convergent and discriminant validity: factor analysis (exploratory factor analysis (EFA)); correlation analysis, and even advanced procedure (e.g. confirmatory factor analysis (CFA) in Structural Equation Modelling (SEM)). For example, to test for convergent and discriminant validity, Kim & Frazier (1997) employ a confirmatory factor model, whereas (Heidi & John (1988) use correlation and regression analysis.

For the purpose of this thesis, convergent and discriminant validity have been assessed by using correlation and performing CFA. Convergent validity is synonymous with criterion with criterion validity (Zikmund 2003). Peter (1981) suggests that a high internal consistency through inter-item correlation (e.g. reliability tests) provides support for construct validity. Correlation analysis is one way of creating construct validity for this thesis. It implies that items that are indicators of a specific construct should converge or share a high proportion of variance in common (Hair et al. 2006). In other words, it assesses the degree to which measures of the same concept are correlated, with high correlation indicating that the scale is measuring it intended concept. Thus, it could be suggested that reliability is also an indicator of convergent validity.

In addition, to demonstrating convergent validity, the magnitude of the direct structural relationship between item and latent construct (or factor) should be statistically different from zero (Holmes-Smith, Cunningham & Coote 2006). The final items (not including deleted items) should be loaded highly on one factor (Anderson & Gerbing 1988), with a factor loading of 0.50 or greater (Hair et al. 2006).

Next, discriminant validity was also used to test construct validity. Discriminant validity refers to the extent to which a construct differs from other constructs (Hair et al. 2006). A measure has discriminant validity when there is a low correlation with measures of dissimilar concepts (Zikmund 2003). High discriminant validity provides evidence that a construct is unique and captures the same phenomenon that was captured by other constructs. Discriminant validity has two methods employed in this thesis: 1) examining the single-factor congeneric model; and 2) conducting CFA. Thus, construct validity was used to enhance the model (through goodness-of-fit results from CFA), and fits to the data adequately (Hsieh & Hiang 2004). Results related to construct validity have been reported in Chapter 6.

4.6.5.2 Reliability

Zikmund (2003) defined reliability as the degree to which measures are free from random error and therefore yield consistent results. In other words, this measure indicates the extent to which the measure is without bias (error free) and hence offers consistent measurement across time and across the various items in the instrument. It helps to assess the goodness of measure, and indicates accuracy in measurement (Sekaran 2003).

This research adopted internal consistency reliability. This type of reliability is used to assess a summated scale where several items are summed to form a total score for a construct (Hair et al. 2006). Hence, the internal consistency reliability was proper with the data of this study (part II in the survey questionnaire), which are in the pattern of a Likert scale. If it is reliable, the items will show consistency in their indication of the concept being measured. This internal consistency reliability is checked by calculating the value of Cronbach's alpha coefficient (Cavana, Delahaye & Sekaran 2001; Hair et al. 2006).

According to Sekaran (2003) and Nunnally (1978), Cronbach's coefficient alpha by Cronbach (1951) is one of the most common methods in assessing reliability. This technique estimates the degree to which the items in the scale are representative of the domain of the construct being measured. It is a measure of the internal consistency of a set of items, and is considered absolutely the first measure one should use to assess the reliability of a measurement scale (Nunnally 1978). In addition, Cronbach's alpha coefficient is important in measuring multi-point scale items (e.g. seven-point Likert scale).

As Cronbach's alpha estimate has been used as a verification of the reliability of the composite items comprising each scale for each construct, in assessing reliability researchers suggest different levels of acceptance. According to Bryman & Bell (2003), the value of Cronbach's alpha coefficient can range from zero (no internal consistency) to one (complete internal consistency). The value of Cronbach's alpha is flattened by a larger number of variables, so there is no set interpretation as to what is an acceptable alpha value. Generally, researchers agree that an alpha value of at least 0.7 is considered acceptable for reliability (De Vaus 2002; Sekaran 2003). However, this may decrease to 0.6 in exploratory research (Robinson, Shaver & Wrightsman 1991a). In addition, Hair et al. (2006) described rules of thumb about the size of Cronbach's alpha coefficient as shown in the following table (see Table 4-8)

Rules of Thumb of Cronbach's Alpha Coefficient	
Alpha Coefficient Range	**Strength of Association**
< 0.6	Poor
0.6 to < 0.7	Moderate
0.7 to < 0.8	Good (acceptable)
0.8 to < 0.9	Very good (acceptable)
> 0.9	Excellent (acceptable)

Source: Hair et al. (2006)

Table 4-8: Rules of Thumb on the size of Cronbach's Alpha coefficient

According to a rule of thumb, the closer Cronbach's alpha Coefficient is to 1, the higher the internal consistency and the more reliable the scale (De Vaus 2002; Hair et al. 2006). In this study, Cronbach's alpha coefficient was calculated for the survey questionnaire for measures of the major constructs of the three main groups of factors: 1) organisational; 2) technological innovation; and 3 environmental characteristics.

Thus, this thesis determined Cronbach's alpha coefficient to ensure that the specified items are sufficient in their representation of the underlying constructs, including the relational groups of organisational innovation adoption. In addition, factor analysis using CFA was used to satisfy correlations among the items and confirm the related concepts. These results are reported in the Chapter 6.

4.6.6 Data Analyses

As pointed out by Coorley (1978, p. 13), "*the purpose of the statistical procedure is to assist in establishing the plausibility of the theoretical model and to estimate the degree to which the various explanatory variables seem to be influencing the dependent variable*". Thus, data analysis by applying quantitative data from the questionnaire survey were analysed by utilising statistical components which were separated into two parts as: 1) preliminary data analysis; and 2) empirical data analysis using structural equation modelling (SEM) to test the hypothesised model discussed in Chapter 3.

The first part was to ensure that the survey questionnaire (instrument) developed for this study produced precise and accurate measurements. This part involved testing the reliability and validity by using the Statistical Package for Social Science version 15.0 (SPSS 15.0) and applying CFA generated in AMOS 7.0 (Analysis of Moment Structures).

These following techniques have been used to apply for the study: Cronbach's coefficient method, descriptive statistics (e.g. minimum, maximum, frequency, percentage, mean, standard deviation, skewness, kurtosis, and Pearson correlation) were involved below (see section 4.6.6.1). In addition, to providing answers to the research questions fully, the second stage was testing the validity of the measurement of the model by performing SEM analysis using the computing power of AMOS 7.0. (see section 4.6.6.2)

4.6.6.1 Statistical Techniques (Part I)

There are three major techniques of statistics performed in this section. These statistical techniques were chosen for the following purposes:

4.6.6.1.1 Cronbach's Coefficient Alpha

To ensure that the instrument developed produced precisely and accurately in terms of measurements, Cronbach's coefficient alpha was selected as an appropriate statistical test for assessing the reliability and validity of the survey questionnaire.

4.6.6.1.2 Descriptive Statistics

Descriptive statistics have a number of benefits: 1) describing the characteristics of the sample; 2) checking variables for any violation of the assumptions underlining the statistical techniques used; and 3) assisting addressing specific research objectives. In term of obtaining the primary information relating to the characteristics of ERP user samples and respondents, using descriptive statics were suitable components. Frequency distributions, percentage, and means were used to describe the data relating to the characteristics of ERP user samples and respondents in Australia.

4.6.6.1.3 The Chi-square Method

The chi-square technique **(χ^2)** was employed to analyse the differences between two groups for the effect of adoption characteristics towards the extent to which those groups use BIDSA, and test hypothesis (H1). In addition, this method also assisted to find the relationship between the effect of two group characteristics and the extent of the use of BIDSA in an ERP perspective.

4.6.6.2 Statistical Techniques (Part II)

The main objective of this research was to generate a model of the adoption of innovation that best described the use of BIDSA by ERP user organisations. In order to achieve this main objective, Structural Equation Modelling (SEM) analysis was considered as the best method.

Structural Equation Modelling (SEM) has become as an important tool (technique) for data analysis in academic research (Anderson & Gerbing 1988; Breckler 1990; Byrne 2001; Hair et al. 2006; Holmes-Smith, Cunningham & Coote 2006; Jöreskog & Sörbom 1996; Kline 2005). In addition, prior researchers also applied SEM as an integral tool in various research areas (e.g. management, IS) such as studies of behaviour (Homburg & Giering 2001), IT development (Koufteros & Marcoulides 2006), and IT systems (Byrd & Turner 2000; Etezadi-Amoli & Farhoomand 1996). The models generated by using multivariate technique, particularly SEM are both substantively meaningful and statistically well-fitting (Holmes-Smith, Cunningham & Coote 2006; Jöreskog, K 1993).

When compared to other multivariate techniques, four significant benefits of SEM (Byrne 2001, 2006) are described as:

- SEM takes a confirmatory approach rather than an exploratory approach to the data analysis.
- SEM can provide explicit estimates of error variance parameters.
- SEM procedure can incorporate both unobserved (e.g. latent) and observed variables.
- SEM methodology has important features (e.g. modelling multivariate relations) for estimating point and/or interval indirect effects.

The primary purpose of SEM is to examine the pattern of a series of inter-related dependence relationships simultaneously between a set of latent constructs, each measured by one or more observed variables (Hair et al. 2006; Schumacker & Lomax 1996). Hence, the SEM technique in this study was used to achieve the objectives as follows:

1) To examine a series of interrelated relationships simultaneously between the analysed dimensions (referred to as non-measurable latent constructs), represented by multiple

variables (referred to as measurable manifest variables) or indicators of the latent constructs.

2) To confirm the theoretical relationships in the models between the latent constructs, and the latent constructs and their indicators, as well as to assess their statistical significance.

Thus, it is an appropriate method for use in this study of information system practises (factors affecting the BIDSA adoption).

In this study, SEM was used as "*a collection of statistical techniques that allow a set of relationships between one or more independent variables, either continuous or discrete, and one or more dependent variables, either continuous or discrete, to be examined*" (Tabachnick & Fidell 2001, p. 653). Hair et al. (2006) mentioned that this technique combines aspects of multiple regression and factor analysis to estimate a series of interrelated dependence relationships simultaneously. Moreover, SEM integrates other techniques (e.g. recursive path analysis, ANOVA, analysis of covariance) (Holmes-Smith 2000). In addition, SEM is also know as path analysis with latent variables and is currently a regularly used approach for representing dependency relations in multivariate data in social sciences (McDonald & Ringo 2002). In other words, SEM represents a model of relationships among variables using a confirmatory approach to the analysis of a structural theory (Byrne 2006). In addition, this conveys two important aspects of the procedure: 1) the causal processes under study are represented by a series of structural equations; and 2) these structural relations can be modelled pictorially to enable a clearer conceptualisation of the theory under study (Byrne 2006).

SEM is based on the assumption of causal relationships where a change in one variable (X1) is supposed to result in a change in another variable (Y1), in which (Y1) affects (X1) (Shammount 2008). Not only does SEM aim to analyse latent constructs, in particularly the analysis of causal links between latent constructs, but also it is efficient for other types of analyses including estimating variance and covariance, test hypotheses, conventional linear regression, and confirmatory factor analysis (Jöreskog & Sörbom 1996). According to Anderson & Gerbing (1988), SEM is a confirmatory method that could provide a comprehensive means for assessing and modifying theoretical models. SEM can generate a statistical test of the goodness-of-fit for the confirmatory factor solution using confirmatory factor analysis (CFA) (Kline 2005).

Arbuckle's (2005) structural equation modelling software AMOS[15] version 7.0 (Analysis of Moment Structures) was used to explore statistical relationships among the items of each factor and between the factors of independent (e.g. benefit, complexity, compatibility, top management support, organisational readiness, absorptive capacity, internal need, competitive intensity, and vendor selection) and dependent variables (e.g. the adoption of BIDSA). AMOS 7.0 computing program (Arbuckle 2005; Arbuckle & Wothe 1999) linked to SPSS was used to conduct SEM analysis. As a result, it becomes the most appropriate widely and easily used package. AMOS can fit multiple models into single analysis. Thus, the study can specify, estimate, assess, and present the appropriate model in a causal path diagram to show hypothesised relationships among variables.

However, as the SEM technique and other statistical methods are alike, some assumptions need to be met before conducting SEM. For instance, the sample size plays an important role

[15] AMOS is an acronym for "Analysis of Moment Structures" or the analysis of mean and covariance structures. AMOS computes parameter estimates so that the resulting implied moments are closet in terms of discrepancy function to the sample moments (Arbuckle 2005).

in the estimation and interpretation of SEM results (Hair et al. 1995). Some authors stated that sample sizes as small as 50 could provide valid results (Anderson & Gerbing 1984; Hair et al. 1998). Hair et al. (2006) argued that there is no correct sample size and suggested that sample sizes in the range of 150-400 are recommended. Boomsma (1983) suggested that the estimation of SEM by using maximum likelihood methods can be used when the sample size was at least 200. Recommended minimum samples of 100-150 could ensure stable maximum likelihood estimation (MLE) solution (Hair et al. 2006). However, the sample size of this thesis is 150, which is considered appropriate for applying the SEM technique.

In order to perform SEM, a two-stage approach is recommended by (Anderson & Gerbing (1988) rather than a single-stage approach. By using this two-stage approach, Kline (2005) stated that the typical problem of not being able to localise the source of poor model fit associated with the single-stage approach is overcome. According to Hair et al. (1998), to avoid any interaction between the measurement and structural models, the two-sage approach offers on accurate representation of the interaction of the reliability of the items of each construct.

Thus, in this thesis, the two-stage approach was adopted to conduct the analysis. That is analysing the causal relationships in the structural model requires performing the measurement model first, due to the latter representing a condition that must be satisfied as a matter of logical necessity (Anderson & Gerbing 1988). The two-stage structural model used in this thesis comprises of 1) measurement model (e.g. assessing unidimensionality and examining reliability and validity); and 2) structural model (e.g. testing hypotheses).

The first stage of analysis was conducted by specifying the causal relationships between the observed variables (items) and the underlying theoretical constructs (composite and latent variables). At this stage, this was to verify the unidimensionality of the composite and latent constructs. Unidimensionality has been defined as "*an assumption underlying the calculation of reliability and is demonstrated when the indicators of the construct have acceptable fit on a single-factor (one-dimensional) model*" (Hair et al. 1998).

However, Anderson & Gerbing (1988) argued that unidimensional measurement models are more generally useful because of models offering more precise tests of the convergent and discriminant validity of factor measurement. Thus, the purpose of this stage is to ensure that a set of items empirically measures a single dimension. In accordance with Anderson & Gerbing (1988), Dunn, Seaker & Waller (1994), and Hair et al. (1998), unidimensionalilty assessment was conducted prior to testing the reliability and validity of each construct.

In assessing unidimensionality, confirmatory factor analysis (CFA) is a better method for use in this research where hypotheses about the grounded theoretical models exist (Bollen 1989), as is the case in the thesis. Kline (2005) also suggested that the factor structure identified in CFA turns out to have best fit when evaluated with CFA. CFA is considered a more powerful (Anderson & Gerbing 1988; Hair et al. 2006) and more flexible (Dunn, Seaker & Waller 1994) technique than others in term of assessment.

Therefore, CFA was used in this thesis. The underlying constructs of relational links (e.g. technology, organisation, and environment characteristics) have already been demonstrated empirically to be valid in the literature. This was to determine whether the number of factors and loadings of measured indicators (items) had conformed to what was expected, based on re-established research and theory. Items that loaded weakly on the hypothesised factors were removed from the scale, thus resulting in a unidimensional scale (Dunn, Seaker & Waller 1994). A factor loading of 0.50 and above on a specified factor has been considered acceptable (Hair et al. 2006). Thus, this standardisation is used as the cut off value within this thesis.

Once the step of undimensionality of constructs is achieved, reliability and validity of these constructs is demonstrated in the following step (see Chapter 6 for further discussion of reliability and validity). For this purpose, CFA using maximum likelihood estimate was performed (Anderson & Gerbing 1988; Kline 2005). Then, the paths or causal relationships between the underlying theoretical latent constructs were specified in the structure model (the second stage). Further details about these two stages are discussed in the following chapter.

The results and also the assessment of data used in the SEM analysis of the relationship between the independent variable and dependent variables are presented in Chapter 5 where discussed are the assessment of normality, outlier, and multicolinearity. Then, Chapter 6 provides the analysis of structural models.

4.7 ETHICAL CONSIDERATION

Before conducting the main survey, the research proposal and survey questions including both questionnaire and interview were submitted to the Human Research Ethics Committee of Victoria University. Approval of the project was granted by this committee of the university to conserve the safety, liberty, and rights of participants before conducting the mail surveys and short interviews.

A cover letter sheet for the survey questionnaire was provided and attached to the questionnaire to explain all objectives of the study (see Appendix A6). Participants were informed that under the research ethics rules, participation was entirely voluntary and that there were no legal, psychological, moral, or other risks. On the other hand, if the participants felt uncomfortably during the study or thought that it was intrusive or were reluctant to provide answers, they could withdraw at any stage of the process.

Complete questionnaires of the survey, transcripts, and tape recordings of the interviews was stored at Victoria University after analysis by the researcher. All data are currently kept at Victoria University and only the researcher and supervisors can access the data. The research results were presented in the form in which participants could be identified.

4.8 SUMMARY

This chapter justifies the need for quantitative analysis to answer the research questions and test the hypotheses. Methodology and methods used were presented including preliminary information gathering, model development, pre-test, pilot study, reliability and validity of the instrument, data collection, and data analysis procedure.
However, to fulfil the purpose of the study SEM is applied as the main statistical technique for the analysis. In addition, regression analysis was performed to test expected relationship differences between the factors, and sub-factors and the construct of the model of BIDSA adoption, early adoption and non-early adoption.

Business organisations selected for this study were Australian ERP user members that have already adopted BIDSA. They were identified utilising the definition of organisations used by the ERP Australian user organizations. The SAP customers provided a total population of 450 of ERP user organizations in Australia.

In this study, the research process was conducted in two stages as follows:

1) The analysis of decision support components of ERP (SAP) users utilising a short interviews instrument to examine the decision support technology features and users' information needs that were available in Australia.
2) The quantitative questionnaire survey was used as the main method to test the model and mainly all of the hypotheses (H1-H5) and contributed to answering requestions 1, 2, 3, and 4.

CHAPTER 5

PRELIMINARY DATA ANALYSIS

5.1 INTRODUCTION

The previous chapter identifies the research methodology along with the justification adopted to test the proposed theoretical model as well as to answer the research questions. In this chapter, there are three main parts: 1) the procedures used for data screening; 2) reliability of the instrument; and 3) the descriptive analysis associated with the response rate and sample characteristics. Thus, according to the schema, the purpose is to present the results of the descriptive statistics used to describe the samples. This preliminary data analysis will be assessed by using descriptive statistical techniques. The results from data analysis in this chapter will fulfil research question (1). In particular, this question aimed to investigate the extent to which BIDSA has been adopted by business organisations in Australia.

5.2 CODING OF MEASUREMENT SCALE FOR BIDSA ADOPTION

This section presents the coding of measurement scales for this study. Table 5-1 below shows the items used in the second part in an instrument. There were approximately 39 scale items in the questionnaires including organizational factors (20 items), technological innovation factors (9 items) and organizational factors (10 items).

Coding of Measurement Scale		
Constructs	**Codes**	**Statements**
Organisational Factors		
Top Management Support	**TOPMS1**	Top management supports the adoption of BIDSA
	TOPMS2	Top management has offered related resources for the development of BIDSA

	TOPMS3	Top management is aware of the benefits of BIDSA
	TOPMS4	Top management provide the cooperation to complete for BIDSA projects
	TOPMS5	Top management recognised and understands knowledge of BIDSA to actively encourage users to use BIDSA
Organisational Size (Resources)	**OSIZE1**	The size of company has a major impact on BIDSA adoption
	OSIZE2	The firm has the technological resources to adopt BIDSA
	OSIZE3	The firm has financial resources to use BIDSA
	OSIZE4	Other organisational resources (e.g. training, IS support, IT governance) helps to build up higher levels of BIDSA adoption
	OSIZE5	Finding all necessary resources (e.g. funding, people, and time) to develop BIDSA is necessary
Absorptive Capacity	**ABSORP1**	Key users of BIDSA are quite familiar with, have a vision for, and understand what it can do for the firm
	ABSORP2	Key users need extensive training to develop to understand and properly use
	ABSORP3	There are hardly any major knowledge barriers in using BIDSA
	ABSORP4	Key users are technically knowledgeable in exploiting BIDSA capabilities
	ABSORP5	There is adequate level of understanding and technical sophistication on the BIDSA users
Internal Need	**NEED1**	BIDSA is needed to improve a timely responding time
	NEED2	The needs to service quality is important for BIDSA
	NEED3	The needs to have cost reducing are required to use BIDSA
	NEED4	BIDSA is needed to provide correct information
	NEED5	BIDSA can help in raising competitive advantages
Technological Innovation Factors		
Perceived Benefits	**BEN1**	BIDSA will enable your company to reduce cost in the operations
	BEN2	BIDSA provides competitive information and improves decision-support operations
	BEN3	The company believes BIDSA will accomplish tasks and enhance business strategies
	BEN4	BIDSA can monitor problems and provide solutions at real-time
Coding of Measurement Scale		
Constructs	**Codes**	**Statements**
Task Complexity	**CPLEX1**	The process of developing (establishing) BIDSA is complicated
	CPLEX2	The operation of BIDSA is considerably to be complicated to implement and use within your firm

	CPLEX3	BIDSA is hard to learn
	CPLEX4	Integrating BIDSA into current work practices will be difficult
	CPLEX5	Considerable resistance exists within the firm toward implementation and use of BIDSA
System Compatibility	**CPAT1**	Using BIDSA fits well with how the company functions.
	CPAT2	Using BIDSA is consistent our compatible firm's value and beliefs
	CPAT3	BIDSA is compatible with the organization's IT infrastructure
	CPAT4	The changes introduced by BIDSA are compatible with existing operating practices
	CPAT5	The connection between BIDSA and data resources in the original computer is important
Environmental Factors		
Competitive Pressure	**CPET1**	The degree of competition in industrial environmental places pressures on the firm to adopt this IT
	CPET2	The firm needs to utilise BIDSA to maintain its competitiveness in the market
	CPET3	The degree of competition in the industrial environment is important to use BIDSA
	CPET4	It is a strategic necessity to use BIDSA
	CPET5	This is a universality of new technology
Vendor Selection	**VEND1**	The vendor's reputation is important to the firm in selecting a BIDSA partner
	VEND2	The relationship with customers is important
	VEND3	The successful experience possessed is important
	VEND4	The capability to plan and complete project is important
	VEND5	The technological competency of consultants is important

Table 5-1: Coding of measurement scale for BIDSA adoption and usage

5.3 DATA SCREENING

According to Tabachnick & Fidell (2001) and Sekaran (2003), data should be examined prior to any data analysis so screening of data is necessary before proceeding to the data analysis stage. Thus, data screening is useful in making sure that data have been correctly entered and in making a distinction between variables that are to be used in the analysis (Coakes 2006).

Screening for accuracy of data entry was undertaken in the case of questionnaire returns. Screening is used to clean the data to a format most suitable for multivariate analysis by using missing data analysis and examination of outlier and data normality. Sethi and King (1991) suggested that data screening could enhance the interpredictability of the results of factor analysis as this research performed CFA analysis. Thus, at the first stage of data analysis, important techniques for screening the data were conducted. These are discussed in the following sections.

5.3.1 Missing Data

It is unusual to obtain data sets without some missing data (Hair et al. 2006). Missing data occur when a respondent fails to answer one or more questions in a survey. Hair et al.(2006) suggested that missing data will impact on the reduction of the sample size available for analysis if the remedies for missing data are not applied. Moreover, any statistical results based on data with a non-random missing data process could be biased if the missing data led to inaccurate results. In addition, in multivariate analysis, the problem of missing data could be mainly with the saturated model and it may be impractical to fit this model. In particular, it is necessary to find missing data where valid values of one or more variables are not available for analysis.

As this research performed structural equation modelling (SEM), Arbuckle (2005) determines the problem of missing data in SEM using AMOS. With incomplete data AMOS cannot provide fit cannot be computed to the entire saturated model by using fit measures (see Chapter 6). Also, AMOS cannot compute the Modification Indices (M.I.), which help to evaluate various potential modifications in a single analysis and direct suggestions for model modifications (Arbuckle 2005). If there are missing values, an attempt to fit these models requires further extensive computation. The reason is because some missing data value patterns can make it impossible to fit the saturated model even if it is possible to fit the potential framework.

Tabachnick & Fidell (2001) recommended evaluation of the degree to which there are missing data because missing data usually occur when a respondent fails to answer one or more questions in the survey. There are two actions that can handle the missing data: delete the cases with the consequence of reducing sample size, or by using a remedy. Hair et al. (2006) recommended the way to identify the patterns and relationships of the missing data to maintain as close as possible the original distribution of values. There are four steps to identify missing data and applying remedies: 1) determine the type of missing data; 2) determine the extent of missing data; 3) diagnosing randomness of missing data; and 4) select the imputation method.

5.3.1.1 Determine the type of missing data

There are two types of missing data: ignorable or not ignorable. Specific remedies for missing data are not needed because the allowances for missing data are inherent in the techniques used (Little & Rubin 2002; Schafer 1997), thus enquiring no remedy (ignorable missing data). However, with the requirement of AMOS, missing data cannot be classified as ignorable as AMOS requires a complete data set. The missing data then cannot be ignored and it is necessary to proceed to the step to determine the extent of missing data. Thus, it is necessary to proceed to the second step to determine the extent of missing data.

5.3.1.2 Determine the Extent of Missing Data

In this step, Hair et al. (2006) suggest that direct means of assessing the extent of missing data are using tabulating: 1) the percentage of variables with missing data for each case; and 2) the number of cases with missing data for each variable. This can be generated by SPSS missing data analysis. In this research, the screening of the data in SPSS indicated that there was no variable that had more than 4% of missing data (see Appendix A7) and since this is less than 5 percent, it can be ignored (Churchill 1995). After using missing data analysis in SPSS (17.0), it was found that the percentage of each variable as missing data was in the range of **0.7**% and **3.3**% and so can be ignored. Thus, there was no requirement to assess the pattern of missing data (Churchill 1995; Tabachnick & Fidell 2001). Using structural equation modelling with the AMOS (7.0) application program as required, the missing data cannot be ignored under any circumstance. Nevertheless, to ensure that there is no systematic error (the missing data were randomly distributed) in the responses, the randomness of missing data is required to be assessed (Hair et al. 2006). Thus, it is necessary to go to the next step.

5.3.1.3 Diagnosing Randomness of Missing Data

In diagnosing randomness of missing data, there are 4 techniques utilized in the SPSS program: 1) Listwise; 2) Pairwise; 3) expectation maximisation (EM); and 4) regression. It is necessary to ensure whether the missing data process shows in a completely random manner. Hair et al. (2006) suggested that even though the sample size is small, it is essential to use a specific statistical program to diagnostic the missing data. In this study, Missing Completely at Random (MCAR), which is sufficiently random to accommodate any type of missing data remedy (Little & Rubin 2002) is appropriate and recommended by Hair et al. (2006).

In this step, Expectation Maximisation (EM) missing data analysis is performed. The EM method is an iterative process to predict the values of the missing variables using all other variables relevant to the construct of interest (Cunningham 2008). The EM analysis estimates missing values by an interactive process which has an “E” step to calculate expected values of parameters and an “M” procedure to calculate maximum likelihood estimates. EM displays means, correlation matrix, and covariance matrix, computed using an EM algorithm. Thus, in this study, Little's MCAR (Missing Completely At Random) (Little & Rubin 2002) test shows **Chi-Square** = 1073.33, Degree of Freedom (**DF**) = 1084, and a significant level (**Sig**) of 0.58. This indicated that no differences were found between the pattern of missing data on most of variables and the pattern expected for a random missing data process. Thus, it can be concluded that missing data can be classified as MCAR and indicated that the widest range of potential remedies can be used.

5.3.1.4 Select the Imputation Method

Due to the requirements of AMOS, the extent of missing data was less than 10%, but this cannot be ignored. In this step, the regression method of imputation is considered to calculate the replacement values based on the rules that the missing data are less than 10 percent (maximum = 3.3%) and classified as MCAR. When using a regression imputation method with SPSS, the variables that will be used in SEM with AMOS data analysis are complete and free of missing data. This indicates that the data are appropriate and ready to be further investigated.

5.3.2 Multivariate Outliers

Following the step of replacement of missing data, the next step is outlier deletion. An outlier is an observation with a substantially different characteristic from the other observations (e.g. it has an extreme value) on one or more characteristics (Hair et al. 2006). A unique characteristic is evaluated to be an unusually high or low value on a variable, or a unique combination of values across various variables that make the observation outstanding from the others. An outlier cannot be categorically characteristics as either beneficial or problematic. However, it must be shown within the context of the analysis and should be evaluated by the types of information provided. Beneficial outliers may be an indication of characteristics of the population that would not be discovered in the normal course of analysis. Conversely, the type of problematic outlier is not representative of the population, is counter to the objectives of the analysis, and could distort statistical tests (Hair et al. 2006).

To test multivariate outliers, it is necessary to calculate the Mahalanobis distance which is the distance of a particular case from the centroid of the remaining cases, where the centroid is the point created by the means of all variables (Tabachnick & Fidell 2001). Mahalanobis (D^2) measure is a mean of multivariate outlier detection to measure the multidimensional position of each observation compared with the centre of all observations on a set of variables.

In multivariate methods, the threshold levels for the D^2 /Df measure should be conservative, resulting in values of 2.5 (small samples – 80 or fewer observations) versus 3 or 4 in larger samples (Hair et al. 2006). In this study, there was no evidence of outliers because the D^2 /Df measure did not exceed the threshold value of 3 or 4 (maximum D^2 = 78.54, degree of freedom (Df) = 40, D^2 /Df = 1.96).

As a result, there were no extreme cases demonstrating the characteristics of outliers because D^2 /Df did not exceed the threshold value. Thus, it was not necessary to delete them from the sample (Pallant 2005). However, with some evidence the possible outlier's data could be retained in the study and this could result in non-normality data and distorted statistics (Hair et al. 2006; Tabachnick & Fidell 2001). In order to check any actual deviation from normality, the techniques of skewness and kurtosis was used in the next section.

5.3.3 Multivariate Normality

The practice of normality involved testing the data for compliance with the statistical assumptions underlying the multivariate techniques and deals with the foundations upon which the techniques make statistical inferences and results. To assess other data screening, normality distribution is important for structural equation modelling so it was necessary to check the distribution of variables to be utilised in the analysis.

Normality is correspondence to the normal distribution which is the benchmark for statistical methods (Hair et al. 2006). As many statistical methods assume that the distribution of scores on the dependent variable is normal, it is used to describe a symmetrical, bell-shaped curve, which shows the greatest frequency of scores in the middle (smaller frequencies towards the extremes) (Gravetter & Wallnau 2000).

To check the actual deviation from normality of this study, three methods were used: 1) univariate skewness; 2) univariate kurtosis; and 3) multivariate kurtosis. These first two techniques were conducted using SPSS. However, the last technique was generated using an AMOS program. Distribution is considered acceptable within a normal range when indicators of the univariate skewness and univariate kurtosis values are less than 2 and 3 respectively (Azzalini 2005; Hair et al. 2006). As the univariate skewness and univariate kurtosis values of the questionnaires were less than 2, this indicates that these values were very small for each item. Thus, these items of the main survey were considered to be normally distributed so suggesting normality. Table 5-2 presents the results of descriptive statistics for the items in this thesis.

As it was necessary to examine the distribution of variables to be utilised in the analysis, it was found that the univariate skewness and kurtosis values of the questionnaires were less than 2 (see Table 5-2). This can indicate that the univariate skewness and kurtosis values were positively small for each item. Initially, there was no severe deviation from normality, therefore, all of these items of the main survey were considered to be normally distributed. However, in multivariate analysis the most fundamental assumption in multivariate is assuming multivariate normality (Hair et al. 2006). It is necessary to assess multivariate normality.

As a result of multivariate normality shown in Table 5-2, most of the multivariate kurtosis values were greater than 1, which presents a problem with implementation when performing SEM. The multivariate kurtosis statistics indicate the extent of departure from multivariate normality. Holmes-Smith, Cunningham & Coote (2006) suggested that values less than 1 are negligible, values from one to ten indicate non-normality while values greater than 10 indicate a more serious problem. Kline (2005) suggested that absolute values of kurtosis index greater than 20 may indicate severe non-normality. However, the AMOS program provides a technique to address this problem. The bootstrapping of an AMOS program incorporates the Bollen-Stine bootstrap method used only for testing model fit under non-normality. This approach to handling the presence of multivariate non-normal data is to use a bootstrap procedure (Yung & Bentler 1996; Zhu 1997). In this case, it is theoretical justified to perform the powerful Bollen-Stine bootstrap method to produce the Bollen-Stine *p* value to be as an alternative *p* value in consideration (Bollen & Stine 1992).

This Bollen-Stine option signifies a modified bootstrap method for the chi-square goodness-of-fit statistic and provides a means of testing the null hypothesis that shows the specified model correctly (Bollen & Stine 1992). A new critical chi-square value is generated against which the original chi-square value is compared. In this research, it was necessary to apply this Boolen-Stine bootstrap technique in the situation of non-normality. The researcher requested AMOS to perform a bootstrap on 150 samples, both within the range suggested by Hair et al. (2006). These results of these tests are presented in the next chapter.

Measures of the Constructs and Descriptive Statistics					
Items	**Means**	**SD**	**Skewness**	**Kurtosis***	**Kurtosis****
Perceived Benefits					
- BIDSA will enable your company to reduce cost in the operations	5.24	1.56	-1.04	.58	1.63
- BIDSA provides competitive information and improves decision-support operations	4.77	1.41	-.80	.10	
- The company believes BIDSA will accomplish tasks and enhance business strategies	4.78	1.67	-.63	-.33	
- BIDSA can monitor problems and provide solutions at real-time	4.77	1.42	-.55	-.34	
Task Complexity					
- The process of developing (establishing) BIDSA is complicated	4.72	1.51	-.53	-.66	15.89
- The operation of BIDSA is considerably to be complicated to implement and use within your firm	4.64	1.47	-.46	-.57	
- BIDSA is hard to learn	4.52	1.42	-.30	-.66	
- Integrating BIDSA into current work practices will be difficult	4.49	1.51	-.26	-.75	
- Considerable resistance exists within the firm toward implementation and use of BIDSA	4.68	1.39	-.56	-.25	
Measures of the Constructs and Descriptive Statistics					
Items	**Means**	**SD**	**Skewness**	**Kurtosis***	**Kurtosis****
System Compatibility					
- Using BIDSA fits well with how the company functions.	4.94	4.18	-.94	.51	11.27
- Using BIDSA is consistent our compatible firm's value and beliefs	4.96	1.49	-.82	.13	
- BIDSA is compatible with the organization's IT infrastructure	4.76	1.65	-.67	-.28	
- The changes introduced by BIDSA are compatible with existing operating practices	4.60	1.44	-.56	-.31	
- The connection between BIDSA and data resources in the original computer is important	4.80	1.38	-.51	-.01	
Top Management Support					
- Top management supports the adoption of BIDSA	4.40	1.65	-.16	-.53	3.29
- Top management has offered related resources for the development of BIDSA	4.66	1.57	-.46	-.42	
- Top management is aware of the benefits of BIDSA	4.45	1.42	-.24	-.48	
- Top management provides the cooperation to complete for BIDSA projects	4.16	1.46	-.17	-.86	
- Top management recognises and understands knowledge of BIDSA in order to actively encourages users to use BIDSA	4.34	1.56	-.28	-.52	
Organisational Size (Resource)					
- The size of company has a major impact on BIDSA adoption	4.39	1.52	-.31	-.53	9.86
- The firm has the technological resources to adopt BIDSA	4.28	1.40	-.12	-.42	
- The firm provide financial resources to adopt BIDSA	4.47	1.35	-.28	-.48	
- Other organisational resources (e.g. training, IS support, IT governance) helps to build up higher levels of BIDSA adoption	4.16	1.59	-.04	-.86	
- There are no difficulty in finding all necessary resources (e.g. funding, people, time) to implement BIDSA	4.51	1.42	-.42	-.52	
Absorptive Capacity					
- Key users of BIDSA are quite familiar with, have a vision, and understand what BIDSA can do for the company	4.54	1.41	-3.0	-.37	

- Key users need extensive training to develop skills and understand and use BIDSA	4.48	1.51	-.24	-.41	
- There are hardly any major knowledge barriers in using BIDSA	4.60	1.60	-.29	-.77	6.96
- Key users are technically knowledgeable in exploiting BIDSA capabilities	3.96	1.47	-0.4	-.62	
- There is adequate level of understanding and technical sophistication on the BIDSA users	4.75	1.41	-.48	-.10	
Internal Need					
- BIDSA is needed to improve a timely responding time	4.67	1.49	-.35	-.51	
- The needs to service quality is important for BIDSA	4.89	1.48	-.69	-.04	
- The needs to have cost reducing are required to use BIDSA	4.73	4.16	-.37	-.50	9.76
- BIDSA is needed to provide correct information	4.44	1.46	-.33	-.65	
- BIDSA can help in raising competitive advantages	4.73	1.47	-.34	-.53	
Competitive Pressure					
- The degree of competition in industrial environmental places pressures on the firm to adopt this IT	4.17	1.56	-.19	-.30	
- The firm needs to utilise BIDSA to maintain its competitiveness in the market	4.45	1.80	-.40	-.87	9.77
- The degree of competition in the industrial environment is important to use BIDSA	4.33	1.57	-.43	-.52	
- It is a strategic necessity to use BIDSA	4.26	1.52	-.27	-.27	
- This is a universality of new technology	4.23	1.25	-.12	-.67	
Vendor Selection					
- The vendors' reputation is important in selecting BIDSA partner	5.03	1.52	-.89	.25	
- The relationship with customers is important	5.02	1.51	-.64	-.20	1.80
- The successful experience possessed is important	4.68	1.56	-.40	-.45	
- The capability to plan and complete project is important	4.55	1.55	-.18	-.75	
- The technological competency of consultants is important	4.77	1.57	-.50	-.54	

* = Univariate Kurtosis

** = Multivariate Kurtosis

Table 5-2: Descriptive statistics and normality distribution in the main survey

5.3.4 Multicolinearity

Multicollinearity is the extent to which a construct can be explained by other constructs in the analysis (Hair et al. 2006). The existence of multicomminearity occurs when the variables that appeared separate, actually measure the same thing. When the dependent variables are highly correlated, it is referred to as multicollinearity. Generally, any two predictors correlated more strongly than 0.70 should be sources of an initial problem and those correlated greater than 0.9 are cause for serious problems (Vogt 2007). According to (Pallant

2005), a correlation of up to 0.8 or 0.9 is reasonable while Hayduk (1987) suggested concerns for values greater than 0.7 or 0.8 (see Table 4-6). However, from the test of reliability it can be seen that some of the variables are highly correlated, which suggests the existence of multicollinearity. Kline (2005) suggested that using elimination of variables be considered for further analysis and also the removal of variable (s) from data analysis is taken in dealing with this technique. This was performed when conducting construct reliability and discriminant validity analysis in the next chapter.

5.4 RELIABILITY AND VALIDITY

There are several different reliability coefficients, however all consistency reliabilities based on Cronbach's alpha for measurement were commonly used and acceptable in the questionnaire survey (Coakes & Steed 2007; Hair et al. 2006). All of them (0.818 - 0.908) were found to be greater than 0.7 (see Table 5-3, next page), which is considered as good acceptability (see the rationale in Table 4-8). All reliability tests were positively acceptable (most greater than 0.8), which indicates that all items in each factor positively correlated to one another (Sekaran 2003). Hair et al. (2006) noted that high construct reliability indicates the existence of internal consistency. In other words, items in each set are independent measures of the same concept, and therefore, indicate accuracy in measurement in the main survey.

In addition, another consistency measure for the survey is the inter-item correlation values, all of which exceed 0.30. It is recommended that the inter-item correlation exceed 0.30 and the item-to-total correlations exceed 0.50 (Robinson, Shaver & Wrightsman 1991). As indicated by Cohen (1988), correlation (r) = 0.10 to 0.29 (small correlation, both positive and negative correlation), r = 0.30-0.49 (medium correlation), and r = 0.50 to 1.0 (strong correlation).

These results support the results of Cronbach's alpha coefficient in that the questionnaire of the main survey was shown as a reliable measurement (the reliability of the research instrument). Thus, according to these guidelines the results of the reliability coefficient were satisfactory for this study.

Reliability Results					
Measurement Items	**Items**	**Cronbach's Alpha**	**Reliability Results**	**Inter-Item Correlation**	**Item-Total Correlation**
Technological Innovation Factors					
Perceived Benefits	4	0.834	**Good**	0.463-0.673	0.581-0.742
Complexity	5	0.879	**Good**	0.448-0.704	0.655-0.773
Compatibility	5	0.884	**Good**	0.411-0.743	0.617-0.836
Organisational Factors					
Top Management Support	5	0.908	**Excellent**	0.621-0.760	0.721-0.824
Organisational Readiness	5	0.843	**Good**	0.413-0.607	0.572-0.725
Absorptive Capacity	5	0.818	**Good**	0.253-0.624	0.519-0.725
Internal Need	5	0.848	**Good**	0.387-0.656	0.598-0.740
Environmental Factors					
Business Competition	5	0.878	**Good**	0.479-0.728	0.632-0.770
Selection of Vendors	5	0.888	**Good**	0.340-0.755	0.615-0.839

Table 5-3: Summary of Cronbach's Alphas, Inter-Item Correlation, and Item-to-Total Correlation in the main survey

Other than the test of reliabilities, another measure to assess validity: convergent validity (correlation analysis), is one way to establish construct validity for the research. Convergent validity assesses the degree to which two measures of the same concept are correlated. According to Hair et al. (2006), high correlations indicate that the scale is measuring the intended concept. The inter-item correlation values of the indicators in the constructs were reasonably high (between 0.25 and 0.76) (except a few inter-item correlation values in some categories). Most of the item-total correlations were positively high (higher than 0.50). Only one item was slightly more than 0.50. Thus, most of the values of inter-item correlation and item-total correlation for the survey were acceptable indicating the convergent validity of the instrument (see Table 5-3).

Another way to conduct construct validity is discriminant validity which will be discussed and presented in detail in chapter 6. According to Table 5-3, items with lower inter-item correlation values will be further investigated using CFA for providing positive validity (see Chapter 6).

5.5 DESCRIPTIVE STATISTICS

As this chapter presents a descriptive analysis of survey data collected over the period May 2008-August 2008, this section is to investigate the extent to which Australian organisations have adopted and implemented BI and decision support applications (BIDSA) in their decision-making activities. Descriptive analysis of demographic data and general analysis were conducted to present the results by using descriptive statistics including frequency, percentage, mean, standard deviation, skewness, and kurtosis. These descriptive statistics are presented in Table 5-2.

5.5.1 Response Rate

A review of the survey literature indicated that there are concerns about the response rates from mail surveys. Achieving a high response rate means less chance of a significant response bias than for a low response rate (Babbie 2004). Cavana, Delahaye & Sekaran (2001) stated that a 30 percent response rate of mail questionnaire is considered acceptable. To achieve the acceptable rate (above 30% response), a follow-up mailing was done to increase the return rate of the mail survey (Babbie 2004). A total of 150 questionnaires were completed and returned as well as positively usable giving a moderately acceptable rate of 33.3 %. Therefore, the sample size of 150 for this study was still sufficient to perform various statistical tests and provide a reliable output and solution (e.g. performing SEM) (Hair et al. 2006).

Questionnaires were distributed to ERP user organizations in Australia that were quite diverse. According to Wong & Aspinwall (2005) and Ramamurthy, Sen & Sinha (2008), it was indicated that the research about IT adoption relating to BIDSA (e.g. KMS, data warehouse technology) categorised profiles of respondent companies into two main industries: 1) manufacturing; and 2) servicing. These will cover sub-industries including chemical, electronic, automotive, machinery equipment, paper/board, consulting, construction, communication, financing, insurance, information technology, transportation, and retailing. Summary profiles of respondent companies are presented in Table 5-4 below.

Summary of Response Rate			
Main types of Industries	**Number of Questionnaires**		
	No. of Questionnaires Received	**Response Rate (%)**	**Total Questionnaires Sent**
Manufacturing (e.g. Chemical, Oil&Gas, Mining, Automotive, Machinery)	**77**	**17.11**	**450**
Servicing (e.g. Retailing, Financing, Insurance, Construction, Transportation)	**70**	**15.57**	
Government Sectors	**3**	**0.67**	
Total	**150**	**33.33**	

Table 5-4: Profiles of respondent companies by types of industries

5.5.2 Profile of the ERP user Samples

In the first part of the questionnaire, the respondents were invited to describe characteristics of their companies. In addition, the respondents were requested to provide their personal characteristics. The reasons for these characteristics being requested were to:

- Provide insights into the composition of the firm samples;
- Allow personal and company characteristics to be related to the extent of use of the business intelligence and decision support applications (BIDSA)

Descriptive statistics in terms of frequencies and percentages were used to describe the characteristics of ERP user samples and company respondents. Table 5-5 below summarises the characteristics of the 150 firms and their respondents in the sample from ERP user samples in Australia.

Profiles of ERP User Samples			
Firm Characteristics	**Categories**	**Responses**	**Percent**
Numbers of Full-Time Employee	1-800 employees	52	34.7
	801-1500 employees	51	34
	More than 1501 employees	45	30
	Not declared	2	1.3
	Total	**150**	**100**
Duration of the Use of Business Intelligence and Decision Support Applications (BIDSA)	Less than 3 years	24	16
	3-5 years	70	46.7
	6-10 years	39	26
	11-15 years	2	1.3
	16-20 years	4	2.7
	Not declared	1	0.67
	Total	**150**	**100**
Level of the Use of Business Intelligence and Decision Support Applications (BIDSA)	Having only basic IS as BIDSA for making a decision	19	12.7
	Having only data warehouse technology as BIDSA	39	26
	Having data warehouse and analytics (e.g. OLAP, DM) as BIDSA	40	26.7
	Having higher level of BIDSA with extended business applications (e.g. CRM, SCM)	38	25.3
	Having the highest level of BIDSA with BI real-time for real-time monitoring	11	7.3
	Not declared	3	2
	Total	**150**	**100**
Level of the Use of Business Intelligence and Decision Support Applications (BIDSA)	Early Adopters of BIDSA	89	59.3
	Non-Early Adopters of BIDSA	58	38.7
	Not declared	3	2
	Total	**150**	**100**
Respondent Characteristics	**Categories**	**Frequency**	**Percent**
Position of Respondents	Chief Information Officer	26	17.3
	IT Project Manager (e.g. BI project)	78	52
	IT Manager	46	30.7
	Total	**150**	**100**
Respondent Characteristics	**Categories**	**Frequency**	**Percent**
Education	TAFE	1	0.7

	Bachelor Master Ph.D.	88 58 3	58.7 38.7 2.0
	Total	**150**	**100**
Duration in Current Position	Less than 1 year 1-3 years 4-5 years More than 6 years **Not declared**	11 93 30 15 1	7.3 62 20 10 0.7
	Total	**150**	**100**
BIDSA Knowledge	Basic BIDSA (e.g. basic decision support IS) Moderate BIDSA (e.g. data warehouse) Advance BIDSA (e.g. data warehouse and other BI applications)	12 54 84	8 36 56
	Total	**150**	**100**

Sources: Data Drawn from survey Questionnaire Responses

Table 5-5: Profiles of company characteristics and respondent characteristics

In terms of the characteristics of the enterprises, more than one third (34.7%) of the sample employed fewer than 800 full time employees, and 34% employed between 801 and 1500. The majority of respondents indicated that more than half (64%) of the sample employed had over 801 full time employees. According to Ramamurthy, Sen & Sinha (2008), up to 800 employees are defined as small to medium sized firms in adopting BIDSA (e.g. data warehouse technology). It is suggested that more than half (64%) of the responding firms are large enterprises. Among this ratio, one possible reason is more likely suggested that these firms would be able to find the resources and afford the investment. Almost half (46.7%) of the use of business intelligence and decision support applications (BIDSA) occurred in the duration of 3-5 years. More than one-quarter (26%) of the sample involved 6-10 years in the use of BIDSA in firms.

In adopting BIDSA, as shown in Table 5-5 more than half (52.7%) of the sample used data warehouse (BI infrastructure) that could support data integration, and analytics (e.g. OLAP, DM) to complete various data analysis for business decision-making. Only 7.3% of the sample used a full range of the BIDSA platform. In other words, there is 12.7% of the sample that had no implemented data warehouse which is a BIDSA infrastructure.

However, according to Table 5-5 classified by adopting conditions (early-adopters and non early-adopters), the majority of ERP user managers indicated that almost three fifth (59.3%) of the early adopters had basic decision support tools, data warehouse, analytics techniques, and extended business applications that can monitor business and provide appropriate solutions at real-time, while approximately a third (38.7%) of the non early adopters had a BIDSA fundamental as data warehouse and with a basic decision support IS.

Among the ERP user organisations that have adopted BIDSA technology (see Table 5-5), the ratio using data warehouse for OLAP and DM (26.7%) is higher than the BI applications with extended applications (e.g. CRM, SCM, BI real-time) (25.3%). One of the possible reasons is that ERP user organisations use BIDSA as a tool for analysing data and important decision-making rather than offering value-added products or services for customers or suppliers by applying CRM or SCM application.

In addition, regarding the demographics of Australian respondents, more than half (52%) stated that they were IT project managers (e.g. decision support or BI project) for the companies in which they worked. The second largest group of the sample was enterprise IT managers (30.7%).

As the results in Table 5-5 suggest, the highest level of education that most Australian respondents completed was a bachelor's degree (58.7%), with 38.7%holding a master's degree. In addition, the managers also provided information about the period of time that they had worked for the organisations in their current position, and the mean was between 1-3 years (62%). The shortest time anyone had held their current position was less than a year (7.3%). The respondents also provided their IT knowledge of BIDSA usage. Not surprisingly the majority of ERP user respondents indicated that their understanding of BIDSA knowledge had been categorised as "knowing BIDSA in term of advance" (56%).

5.5.3 The Extent of Use of BIDSA in ERP User Organisations

The purpose of this part of the study is to examine the similarities and differences between the use of BIDSA and ERP user characteristics in terms of size of organisations, industry characteristics of companies, and duration of using BIDSA on the extent of use of BIDSA. The results were used to answer research question (1) and to test hypothesis (H1). Pearson chi-square was chosen to test any significant differences and the results are summarised in the following table (see Table 5-6).

Characteristics of an ERP User and the Extent of Use of BIDSA			
Size	**Early Adopters ERP Firms**	**Non-early Adopters ERP firms**	**Total**
Small and Medium (1-800)	24 (47.1%)	27 (52.9%)	51 (100%)
Large (Over 800)	63 (67.0%)	31 (33.0%)	94 (100%)
Total	87	58	145 (100%)
Pearson Chi-Square (χ^2) = 5.490, Df = 1, *p*-value = 0.019 (Sig. 2-sided)			
Duration of Using BIDSA	**Early Adopters ERP Firms**	**Non-early Adopters ERP firms**	**Total**
1-5 years	54 (51.9%)	50 (48.1%)	104 (100%)
More than 5 years	35 (81.4%)	8 (18.6%)	43 (100%)
Total	89	58	147 (100%)
Pearson Chi-Square (χ^2) = 11.062, Df = 1, *p*-value = 0.001 (Sig. 2-sided)			
Industry	**Early Adopters ERP Firms**	**Non-early Adopters ERP firms**	**Total**
Manufacturing	46 (48.0%)	30 (52.0%)	76 (100%)
Servicing	42 (60.0%)	26 (40.0%)	68 (100%)
Public Sectors	1 (33.3%)	2 (66.7%)	3 (100%)
Total	89	58	147 (100%)
Pearson Chi-Square (χ^2) = 0.972, Df = 2, *p*-value = 0.615			

Table 5-6: Characteristics of an ERP user organisation and the extent of use of BIDSA

When comparing the size of ERP user organisations and the extent of use of BIDSA, the results in table 5-16 show that there was a significance difference in the extent of use of BIDSA between organisations in terms of size (small and medium-sized (SME) and large-sized scales) (χ^2= 5.490, Df. = 1, *p*-value= 0.019). Based on these results, this finding indicated that more of early adopter firm sizes were larger than size of non-early adopter firm. However, about equal percentage of early adopters and non-early adopters were small and medium firms (47.1% and 52.9%, respectively). Both small and medium-sized ERP user organizations in Australia were more likely to be less receptive to the use of BIDSA at both early adopters and non-early adopters than large-sized ERP user firms.

In addition, findings from this study show that the majority of the ERP user organisations in the sample were large-sized companies, which could positively provide more resources for investing in more advances of BIDSA components (early adopters) (see percentage in early adopter ERP users column). It was suggested that larger enterprises usually have sufficient resources to compensate for the accompanying limitations of large expenses and labour required in adopting and implementing BIDSA. This was similar to the characteristics of the organisation based on size of businesses in Hwang et al.'s (2004) and Buonanno et al.'s (2005) study in adopting the more advance IT systems.

When comparing the time duration in using BIDSA and the extent of use of BIDSA, the results in Table 5-6 show that there was a significant difference in the extent of use of BIDSA between the ERP user organisations in the time duration of 1-5 years and over 5 years (χ^2 = 11.062, Df = 1, *p*-value = 0.001). The results showed that significantly more ERP users at the early adoption stage (81.4%) had more than 5 years of adoption and implementation of

BIDSA compared with non-early adopters (18.6%). Based on these results, the findings seem to suggest that time consumed in the BIDSA project is important. More than three-fourths of ERP users implementing IT relating to BIDSA over 5 years (81.4%) have implemented the full range of BIDSA applications, whereas approximately 50% of ERP users with 1-5 years of BIDSA adoption have had the same components of the BIDSA platform. It seems that this may be because the full range of BIDSA components took a longer time to become comprehensive and developed with the full capability of BIDSA (Hawking, Foster & Stein 2008), but there may also be other factors, possibly the readiness of resources of each organisation, which were similar to the previous studies in Chapter 2. The specific finding of the level of the use of BIDSA indicated that most BIDSA users who were early adopters have made full of use of BIDSA capability. This was not similar to the study by Foster, Hawking & Stein (2005). This finding could suggest that innovation diffusion can assist ERP users adopt and implement more advances in BIDSA technology as shown in a number of those in the stage of early adoption. However, no significance was found in the differences between stages of adoption and types of industry.

Based on these findings there were significant differences in the characteristics of ERP user organisations and the extent to which an organisation used BIDSA. However, there was no significant difference between a firm's industry type organizational innovation adoption. These provide partial support for hypothesis (H1): there is a difference reflected in terms of size and time duration using BIDSA. In addition, as theorised in chapter 3 the extent of BIDSA was identified at early and non-early adopting level. These findings also provide partial support for the research question (Q2): there is a difference in the effects of factors: 1) organisational, 2) technological innovation and 3) environmental on the adoption of BIDSA between early adopters and non-early adopters.

5.6 SUMMARY

This chapter has presented and described the demographic characteristics of the research samples along with information concerned with the respondents' profiles. As the response rate was sufficient to perform multivariate analyses, recommended minimum sample size of 150 is considered as stable for achieving related techniques using in multivariate analyses. Reliability and validity of the measures of motivational factors for the adoption of BIDSA have been described and satisfied as well as acceptable. All of these items showed normal distribution when univariate skewness and univariate kurtosis were employed. However, the values of multivariate kurtosis did not show normal distribution. Background information has illustrated the level of BIDSA use among Australian organisations including demographic and organisational characteristics. Most respondents in ERP user organizations had graduate degrees (both bachelor and master, 58.7% and 38.7% respectively) while most were categorised as "more advance BIDSA knowledge" in having the understanding of BIDSA knowledge (56%). Most were IT project managers (52%). The level of the use of BIDSA indicated that the majority of BIDSA users who were early adopters (59.3%) have made full of use of BIDSA capability. In addition, the results of cross-tabulation analyses showed that there are relationships between the company's characteristics and the level of BIDSA usage. It is suggested that the organisational characteristics in terms of business scale and the duration in using BIDSA indicate the significant differences in the extent of the use of BIDSA.

The next chapter provides a successful model by using the techniques of multivariate analysis and performing structural equation modelling (SEM) to empirically examine and test the hypotheses of relationships between potential innovation factors for BIDSA adoption.

CHAPTER 6

STRUCTURAL EQUATION MODELING: BIDSA ADOPTION MODELS (BIAM)

6.1 INTRODUCTION

In chapter five, descriptive statistics of the demographic data of the respondents as well as the procedure of reliability analysis were described. This stage is to investigate what significant determinants influence BIDSA adoption as these factors have a potential role in explaining the adoption: to examine whether the main group of constructs: 1) technological innovation factors; 2) organisational factors; and 3) environmental factors influence the predictors toward adoption. The purpose of this chapter is to empirically examine and test the hypotheses of relationships between the potentially relational factors for the adoption of BIDSA. The causal relationships of determinants (predictors) and adoption could be examined by applying multivariate analysis using structural equation modelling (SEM) (Hair et al. 2006).

As discussed in chapter four, the quantitative method using a questionnaire survey was chosen as an appropriate way for the second stage of this study. Specifically, performing SEM was used as the main method to test the model and all of hypotheses (H2xi, H3xi, and H4xi) (xi represents a number of sub hypotheses), and answer the research questions (2, 3, and 4), mentioned in Chapter 1 and 3.

6.2 CONSTRUCTS OF THE RESEARCH

This research model contains four main groups of latent constructs. A latent construct is the operationalisation of a construct in structural equation modelling (SEM). A latent construct is also known as a latent variable or factor. Latent constructs cannot be measured directly but can be represented or measured by one or more variables (indicators) (Hair et al. 2006). In SEM methodology, an observed variable serves as an indicator of the underlining constructs (Byrne 2006). An observed (measured) variable is a specific item obtained from respondents (e.g. questionnaires, observations). This variable is used as an indicator of latent constructs that are associated with each latent construct and specified by the researcher (Hair et al. 2006).

In this research, the four main groups of latent constructs consist of three main exogenous variables and an endogenous latent variable. However, nine factors (constructs) could all be indicated as main constructs for exogenous constructs. An exogenous construct is a latent, multi-item equivalent of an independent variable. This type of construct is not affected by any other construct in the model. Conversely, an endogenous construct is a latent, multi-item equivalent to dependent variables that are affected by other constructs in the model (Hair et al. 2006; Sharma 1996).

In this study, how to consider which items belongs to a specific latent construct was derived from the literature (e.g. BuonannoFaverioPigni Ravarini 2005; Gatignon & Roberston 1989b; Grandon & Peason 2004; Haley 1997; Hwang et al. 2004; Iacovou, Benbasat & Dexter 1995; Lee & Shim 2007; Lee & Shim 2007; Mehrtens, Cragg & Mills 2001; Rai & Bajwa 1997; Ramamurthy, Sen & Sinha 2008; Thompson, Lim & Fedric 2007; Thong 1999; Watson, Rainer Jr. & Koh 1991). There are “no hard-and-fast rules” guiding the decision for keeping a measure short which is an effective means of minimizing response biases caused by boredom or fatigue (Schriesheim & Eisenbach 1990). Each factor (construct) comprises at least four items (indicators/observed variables) and no more than five items (Harvey, Billings & Nilan 1985). Bentler & Chou (1987) suggest the necessary number of items per factor should contain three to five indicators to measure each factor. This is because the interpretation of results and their statistical significance become difficult when the number of concepts becomes too large (Reisinger & Turner 1999, 2000). For example, according to Table 6-1, as on exogenous variable in this study, perceived benefits is measured by four items comprising of TECH1 to TECH4, followed by task complexity measured by five items comprising of TECH5 to TECH9. In addition, the endogenous variable is the adoptions of BIDSA. This was measured in five items (indicators) which consist of five level of adoption as ADOPT1 to ADOPT5.

Each factor (or construct) comprises at least four items (indicators/observed variables). Table 6-1 in the next page summarizes the ten latent variables.

Four Constructs and Ten Factors in the research model					
Main Constructs	**No.**	**Constructs/ Factors**	**Items/ Indicators**	**Codes/Name of Construct (Factors)**	**Definitions of the Constructs (Factors)**
1 Technology (TECH)*	1	Benefit	TECH 1-TECH 4	BEN	Perceived Benefits
	2	Complexity	TECH 5-TECH 9	CPLEX	Task Complexity
	3	Compatibility	TECH 10-TECH 14	CPAT	System Compatibility
2 Organization (ORG)*	4	Top Management Support	ORG 1-ORG 5	TOPMS	Top Management Support
	5	Organizational Size	ORG 6-ORG 10	OSIZE	Organizational Size (Resources)
	6	Absorptive Capacity	ORG 11-ORG 15	ABSORP	Absorptive Capacity
	7	Internal Need	ORG 16-ORG 20	NEED	Internal Need
3 Environment (ENV)*	8	Competitive Pressure	ENV 1-ENV 5	CPET	Competitive Pressure
	9	Vendor Selection	ENV 6-ENV 10	VEND	Vendor Selection
4 Adoption**	10	BIDSA Adoption	ADOPT1-ADOPT5	ADOPT	Level of BIDSA Adoption

* = Exogenous Latent Constructs

** = Endogenous Latent Constructs

Source: Thong (1999); Rogers (1995); Hwang et al. (2004); Ramamurthy, Sen & Sinha (2008); Thompson, Lim & Fedric (2007); Ikart & Ditsa (2004); Buonanno et al. (2005)

Table 6-1: Constructs (factors) in the research model

In order to perform the SEM analysis in this study, the two-step approach recommended by Anderson & Gerbing (1988) was applied. This two-stage approach was used in order to avoid the inability to identify the source of a poor model fit in relation to the single-stage method (Kline 2005). The steps of this two-stage approach involves: 1) the evaluation of measurement models to ensure that indicators (factors) used to measure each of the constructs are adequate; and 2) the assessment of the structural model which shows the relationship between the constructs (Anderson & Gerbing 1988). However, before continuing to the SEM approach, it is necessary to assess the reliability and the validity of the constructs. Reliability and validity are separate but closely related conditions (Bollen 1989). Both important measures will be discussed and presented in the following sections.

6.3 CONSTRUCT RELIABILITY

As reliability is the consistency of measurements, construct reliability measures the internal consistency of a set of measures which capture the degree to which a set of measures indicate the latent constructs (Hair et al. 2006). This measure provides the estimation of a congeneric measurement model, confirmatory factor analysis or path model with latent variables (Holmes-Smith, Cunningham & Coote 2006). As discussed in chapter 4, the assessment of construct reliability was conducted by examining the Cronbach's alpha coefficient of each construct (factor). Based on Table 5-3 (see section 5.4), it has been suggested that each construct has good reliability because their Cronbach's alpha coefficient values were higher than 0.8, which are generally acceptable for high reliability (Hair et al. 2006; Sekaran 2003).

More importantly, reliability does not confirm validity. A measure may be consistent (reliable) but not accurate (valid). This means a measure may be accurate but not consistent

(Holmes-Smith, Cunningham & Coote 2006). The next step after examining construct reliability is the assessment of discriminant validity. However, it is important to investigate the measure of model fit because this is used to assess the goodness-of-fit of the model.

6.4 MEASURE OF FIT

It is necessary to understand how to evaluate the model before analyzing the structural model. One of the important aims in the application of the SEM approach is the assessment of the goodness of fit. Hair et al. (2006) noted that SEM has no single statistical test that could best describe that strength of the model's predictions. There are many indices of SEM but there is no concurrence among scholars as to which fit indices should be officially used. For example, Cunningham (2008) and Kline (2005) recommended that basic measures to evaluate a model's fit are the chi-square $[(\chi]^2)$ test and the associated *p*-value. Many scholars reported that fit measures are categorized as various types and each type has its specific capability in term of model evaluation (e.g. measures of parsimony, minimum sample discrepancy function, comparison to a baseline model, a goodness of fit index (Arbuckle & Wothe 1999; Bollen & Long 1993; Byrne 2001, 2006; Jaccard & Wan 1996; Kline 2005).

However, Kline (2005) recommended that at least four types are important: GFI; NFI or CFI, NNFI; and SRMR. In order to reflect diverse criteria and provide the best picture of the model fit, there are at least three fit indices as exhibited in Table 6-2 by including one in each of the categories of model fit: absolute measure; incremental measure; and parsimony fit measure (Byrne 2001; Cunningham 2008; Hair et al. 2006; Kline 2005). Suggested by Holmes-Smith (2000) among the many measures of fit, five popular measures are: Chi-square, normed chi-square $\frac{[(\chi]^2)}{df}$, goodness of fit index (GFI), Tucker-Lewin index (TLI), Root Mean-Square Error of Approximation (RMSEA). However, all fit measures in Table 6-2 are used to evaluate goodness-of-fit of the model in this research. These are described in more detail below.

Summary of Goodness-of-Fit Indices		
Name of Index	**Level of Acceptance**	**Fit Measures' Indications**
1. Absolute Fit Indices		
1.1 Chi-square (χ^2)	$p > 0.05$	p = p value greater than 0.05 indicates an acceptable fit
1.2 Goodness-of-Fit (GFI)	Greater than 0.90	A value close to 0 indicates a poor fit, while a value close to 1 indicates a perfect fit
1.3 Root Mean Square Error of Approximation (RMSEA)	$0.05 \leq \text{RMSEA} \leq 0.08$	A value should not be greater than 0.1
2. Incremental Fit Indices		
2.1 Adjusted Goodness-of-Fit (AGFI)	Greater than 0.90	Value close to 0 indicates a poor fit, while value close to 1 indicates a perfect fit
2.2 Tucker-Lewis Index (TLI)	Greater than 0.90	A value close to 1 indicates a good fit
2.3 Norm Fit index (NFI)	Greater than 0.90	A value between 0 and 1, while 1 indicates a perfect fit
2.4 Comparative Fit Index (CFI)	Greater than 0.90	A value between 0 and 1, while a value close to 1 indicates the best fit
3. Parsimonious Fit Indices		
3.1 Normed Chi Square (χ^2 /df or CMIN/df)	$1.0 \leq \chi^2 /\text{df} \leq 5.0$	Lower limit is 1.0, upper limit is 3.0 or as high as 5.0

Table 6-2: Summary of Goodness-of-Fit Indices used in this research

Summarized from Table 6-2, the first group is absolute fit indices. The chi-square (χ^2) is considered the most fundamental measure of overall fit (Bollen 1989; Jöreskog 1969). First, the chi-square statistic is an overall measure of how many of the implied moments and sample moments differ. The more implied and sample moments differ, the bigger the chi-square statistic, and the stronger the evidence against the null hypothesis. This is the most common and basic measures to evaluate a model's fit and the chi-square test is associated with its *p* value (Kline 2005). A statistically non-significant chi-square ($p > 0.05$) value should be observed to indicate good fit (Hair et al. 2006).

However, Marsh, Hau & Wen (2004, p. 336) showed that the chi-square statistic (when the data were generated with multivariate normal distributions and maximum likelihood estimation was performed) "*consistently outperformed all of the goodness-of-fit indexes in terms of correctly rejecting misspecified models*", while accepting 'true' models. Because of extraneous influences on the magnitude of the chi-square approximation (e.g. sample size, number of parameters), Jöreskog (1977) and others (Bentler & Bonett 1980) have suggested that a strict interpretation of the chi-square generated by model estimation should be abandoned, or minimally, interpreted in light of indexes of comparative fit. The sample size is criticized for being too sensitive for this measure to evaluate the model fit (Jöreskog & Sörbom 1996; Marsh, Balla & McDonald 1988), probably in cases where sample size is sensitive (both small and large) (Bagozzi & Yi 1988; Hair et al. 1998).

The chi-square statistic nearly always rejects the model when large samples are used (Bentler & Bonett 1980; Jöreskog & Sörbom 1993). When small samples are used, the chi-square statistic lacks power and because of this may not discriminate between good fitting models and poor fitting models (Kenny & MaCoach 2003). Based on previous studies, the chi-square is always referred to as either a "badness of fit" or a "lack of fit" (Kline 2005; Mulaik et al. 1989). Even though it has been suggested that the chi-square test and the associated *p*-value is the most common and basic measures to evaluate a model's fit (Cunningham 2008; Kline 2005), it alone should not be used as a test of validity of a model (Hair et al. 1998) since it loses validity.

Passing a chi-square test does not mean the model is necessarily correct (Mulaik 2007). The researchers suggested that SEM studies with samples of 200 or less should not originarily be appropriate and power analyze against meaningful alternative indices should be considered

(Barrett 2007; Mulaik, S 2007). As this research performed SEM by using samples of 150, suggested alternatives are that researchers should report the parsimony ratio (Bullock, Harlow & Mulaik 1994; Carlson & Mulaik 1993; Mulaik 1988) along with indices of approximate fit so that one can evaluate the degree of fit in the light of the degree to which the model was tested by the data. An extra of comparative fits indexes has been proposed as measures of adjuncts to the chi-square approximation (Marsh, Balla & McDonald 1988).

As a insignificant chi-square normally indicates a good fit, but this is difficult to achieve with the sample size sensitivity because a chi-square test will detect even minute differences between the hypothesized model and the data (Bollen & Long 1993; Browne & Cudeck 1993; Hayduk 1987, 1996), the researcher also considered other indices of fit that are relatively unaffected by sample size (Jöreskog 1993). Thus, the chi-square measure was not used to reject or accept the model, but used in conjunction with other indices to evaluate overall fit (Bagozzi 1981; Barrett 2007). From Table 6-2, it can be seen that the other fit measures also indicate the goodness-of-fit of the model to the data (Mulaik 2007).

Second, the Goodness-of-Fit Index (GFI) measure indicates the relative amount of variance and covariance together explained by the model (Byrne 1989). This value is calculated by comparing the discrepancy value for the model under test to the discrepancy value for a saturated version of the model which is counted as representing a perfect fit (or 1.0). Nevertheless, this measure is not adjusted for degree of freedom (Hair et al. 1998), ranging from 0 (indicating a poor fit) to 1 (indicating a perfect fit), where a recommended level of acceptance is greater than 0.90 (Hair et al. 1998).

In addition, Root Mean Square Error of Approximation (RMSEA) assists in correcting the tendency of chi-square to reject specified models. It takes into account errors of approximation in the population, and relaxes the stringent requirement that the model holds exactly in the population. Holmes-Smith, Cunningham & Coote (2006) recommended that RMSEA should be less than 0.05 to be considered as indicative of good fit (Browne & Mels 1990), while MacCallum & Browne (1993) suggested a value of up to 1.0. However, Hair et al. (2006) and Browne & Cudeck (1993) proposed that a value ranging from 0.05 to 0.08 is acceptable as "values up to 0.08 represent reasonable errors of approximation in the population" (Jöreskog & Sörbom 1996). Thus, RMSEA is a measure of the discrepancy per degree of freedom; the smaller it is the better as it is one of the fit indexes that are less influenced by sample size.

The second group of indices is incremental fit measures. These measures provide a comparison between the proposed model and the null model[16]. Adjusted Goodness-of-Fit Index (AGFI) is first of the incremental indices. This measure takes into account adjustment for degrees of freedom (*df*), which GFI from the absolute fit indices category cannot do (Hair et al. 1998; Holmes-Smith, Cunningham & Coote 2006; Marsh, Balla & McDonald 1988). The quantity "1-GFI" is multiplied by the ratio of the model's *df* divided by *df* for the base line model, the AGFI is 1 minus this result. Similar to GFI, these ranges from 0 (indicating a poor fit) to 1 (indicating a perfect fit), where a recommended level of acceptance is greater than 0.9 (Hair et al. 1998).

In addition, the measure of Normed Fit Index (NFI) is another popular incremental measure (Byrne, B.M. 2001; Hair et al. 1998). This measure reflects the proportion to which the

[16] Hair et al. (1998) define null model as baseline or comparison standard used in incremental fit indices.

researchers' model fit compared to the null model. If NFI is equal to 0.50, it means the researchers' model improves fit by 50 percent. However, this index does not control for degrees of freedom (Bollen 1989). Bentler (1990) overcame this with the Comparative Fit Index (CFI). CFI compares the covariance matrix predicted by the model to the observed covariance matrix. Thus, both measures (NFI or CFI) are considered in this thesis. Both of them range from 0 (indicating a poor fit) to 1 (indicating a perfect fit) having a commonly recommended level of 0.90 or greater (Hair et al. 1998). The last measure is Tucker-Lewis Index (TLI), which is known as a nonnormed fit index (NNFI) (Hair et al. 1998; Marsh, Balla & McDonald 1988). This combines a measure of parsimony into a comparative index between the proposed or hypothesized and null models, resulting in values ranging from 0 (indicating not fit) to 1 (indicating a perfect fit). The commonly recommended level is 0.90 or greater (Hair et al. 1998). Moreover, it provides a nonbiased indication of models for at all sample sizes (Finch & West 1997).

The third category is Parsimonious Fit Indices, which tests the parsimony[17] of the proposed model by evaluating the fit of the model to the number of estimated coefficient required to achieve the level of fit (Hair et al. 1998). In this section, only Normed Chi-Square (χ^2 /df or CMIN/df) is the most popular parsimonious fit index used to evaluate the appropriateness of the model (Hair et al. 1998). Ranging from less than 2.0 (Bollen 1989; Hair et al. 1998; Tabachnick & Fidell 2001), through less than 3.0 (Carmines & McIver 1981), to more liberal limits of less than 5.0 (Wheaton et al. 1977) are a range of acceptable values for the χ^2 /df ratio. Since χ^2 is the main component of this measure, χ^2 /df is also sensitive to the sample size. Therefore, this measure was used as an indicator of overall fit (in conjunction with other measures), not as a basis for rejecting or accepting the model.

[17] Hair et al. (1998) define the parsimony as the degree to which a model achieves model fit for each estimated coefficient. The purpose is not to minimise the number of coefficients or maximise the fit. However, it is to maximise the amount of fit per estimated coefficient.

Apart from them, bootstrapping (analysis function) is a versatile method for estimating the sampling distribution of parameter estimates (Arbuckle 2005). This option signifies a modified bootstrap method for the chi-square goodness-of-fit statistic, and provides a means of testing the null hypothesis that the specified model is correct (Bollen & Stine 1993). The bootstrapping procedure computes a new critical chi-square value that represents a modified chi-square goodness-of-fit statistic. To show a good-fitting model, the Bollen-Stine *p* value is suggested as "larger is better" (Bollen & Stine 1993; Chin & Todd 1995). In this research, it is important to use this Bollen-Stine bootstrap method in the situation of non-normality. According to Hair et al. (2006), the researcher performed AMOS to implement a bootstrap on 150 samples suggested within the range as sufficient. In this research as seen in Table 5-2, the values of multivariate kurtosis indicated that all of the absolute values of the kurtosis index greater than 1 may indicate non-normality. Thus, it is necessary to apply the Bollen-Stine bootstrap method in the situation of non-normality to support the indication a model fit (see section 6.5.1). Therefore, as mention earlier in this section, all the above criteria were applied to use in this research to evaluate fit of the models.

6.5 DISCRIMINANT VALIDITY

Discriminant validity is the accuracy of a measure to assess the validity where the constructs are interrelated. This reflects the extent to which the constructs in a model are different. Large correlations between latent constructs showing greater than 0.8 or 0.9 suggested a lack of discriminant validity (Holmes-Smith, Cunningham & Coote 2006). This research used pattern and structure coefficients in determining whether constructs in the measurement models are empirically distinguishable. Pattern coefficients are standardized factor loadings derived from AMOS analysis. Prior to analysis of the structural equation model, all its variables were examined for relevance. Thus, SEM techniques using the two-step technique can be used to estimate discriminant validity (Anderson & Gerbing 1988). This method comprises:1) examining the single-factor congeneric model; and 2) conducting CFA.

6.5.1 Discriminant Validity Using Single-Factor Congeneric Model

Based on the responses received from IT managers of ERP user organizations (N=150), one factor congeneric models using maximum likelihood CFAs were initially evaluated for the hypothesized latent constructs of benefit, complexity, compatibility, top management support, organizational size (resource), absorptive capacity, internal need, competitive pressure, and vendor selection as well as adoption. A congeneric model (measurement model) is a model that specifies a prior the posited relations of the observed measures to latent variables representing underlying constructs (factors) (Cunningham, E 2008). Analysis of congeneric models using AMOS 7.0 allow for complex modeling whereby error associated with the measurement of latent variables can be developed, and the fit of these indicators as measures of the latent variables can be tested. The variances of latent variables in these models were set to unity for specifying the models. This measurement model identifies and tests the relationships between observed measures and their underlying constructs (first stage) and provides a confirmatory assessment of construct validity (Bentler 1978). Anderson & Gerbing (1988) argued that uni-dimensional measurement models are more generally useful because of offering more precise tests of convergent and discriminant validity of factor measurement. It measures a construct's uni-dimensionality, which can be from the absence of correlated error items (Cunningham 2008). The goodness-of-fit of the single-factor congeneric model provides a CFA test of the discriminant validity of the construct.

In this study, ten single-factor congeneric models of the latent variables were examined: 1) benefit (BEN); 2) task complexity (CPLEX); 3) system compatibility (CPAT); 4) top management support (TOPMS); 5) organizational size (OSIZE); 6) absorptive capacity (ABSORP); 7) internal need (NEED); 8) competitive pressure (CPET); 9) vendor selection (VEN); and 10) BIDSA Adoption (ADOPT).

6.5.1.1 Confirmation of the Benefit Construct

A one-factor congeneric model of benefit was found to provide a good fit of model to the data (see Figure 6-1 below). The model in Figure 6-1 yields a χ^2 (chi-square) of 3.017, df = 2, and *p* value = 0.221 (Bollen-Stine bootstrap *p*= 0.245 which is not significant at level of 0.05). In addition, it is also indicated by the significance by CMIN/df = 1.509, GFI = 0.990, AGFI = 0.990, TLI = 0.986, CFI = 0.995, and RMSEA = 0.058. All remaining items loaded highly on this factor, as factor loading ranged from a low of 0.64 to a high of 0.83, which suggests that these coefficients are of reasonable magnitude (e.g. exceed at 0.40) (Cunningham 2008) (see Figure 6-1). Thus, since the model fit the data very well, no further examinations to be investigated for removing items unfitted are necessary.

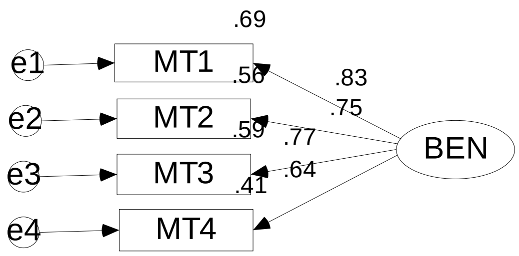


Figure 6-1: Congeneric model of benefit

	Estimate	S.E.	C.R.	P
T4 < --- BEN	1.000			
T3 < --- BEN	1.413	.193	7.330	***
T2 < --- BEN	1.157	.156	7.417	***
T1 < --- BEN	1.423	.188	7.580	***

*** = Significant at $p < 0.001$

Table 6-3: Regression weights of benefit construct

All the regression weights in Table 6-3 were significant at the level with $p < 0.001$

6.5.1.2 Confirmation of the Task Complexity Construct

As shown in Figure 6-2, the initial model for the one-factor congeneric model of task complexity was found to show a good fit of the to the data: χ^2 (chi-square) of 9.819, df = 5, and *p* value = 0.081 (Bollen-Stine bootstrap *p* = 0.159). In addition, other fit measures also indicate the goodness of fit as CMIN/df = 1.964, GFI = 0.908, AGFI = 0.930, TLI = 0.977, CFI = 0.989, and RMSEA = 0.080. The factor coefficients in Figure 6-2, ranged from a low of 0.68 to a high of 0.95. Therefore, items would likely be retained because the model was shown a good fit to the data.

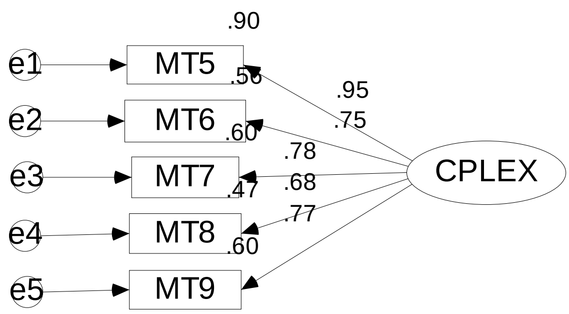


Figure 6-2: Congeneric model of task complexity

	Estimate	S.E.	C.R.	P
T8 < --- CPLEX	1.000			
T7 < --- CPLEX	1.066	.121	8.781	***
T6 < --- CPLEX	1.063	.126	8.458	***
T5 < --- CPLEX	1.384	.136	10.213	***
T9 < --- CPLEX	1.043	.121	8.638	***

*** = Significant at *p* < 0.001

Table 6-4: Regression weights of task complexity construct

All the regression weights in Table 6-4 were significant at the level with *p* < 0.001.

6.5.1.3 Confirmation of the System Compatibility Construct

For the construct of system compatibility, an examination of the modification indices of the one-factor congeneric model for the construct of system compatibility revealed that covariances eCPAT3 and eCPAT4 might be modified. The modification indices in AMOS 7.0 showed high covariance between the third and fourth measurement errors. Common methods of re-specifying the model include: dropping one or both of the items as measures of task compatibility, or covarying the error terms (Holmes-Smith, Cunningham & Coote 2006). The third question (MT12) associated with the fourth measurement error was deleted as it was redundant with the fourth item (MT13).

While the initial model for the latent variable of system compatibility resulted in a poor fit of the model to the data, as a consequence of dropping an error covariance, as shown in Figure 6-3 the re-specified model indicated that the model was a good fit to the data: χ^2 (chi-square) of 4.500, df = 2, and *p* value = 0.105 (Bollen-Stine bootstrap *p* = 0.192). It also indicated the good fit in terms of: CMIN/df = 2.250, GFI = 0.985, AGFI = 0.924, TLI = 0.967, CFI = 0.989, and RMSEA = 0.092. After the revised measurement model was tested with a new sample recommended by Thompson (2000), all remaining items loaded highly on this factor, as factor loading ranged from a low of 0.62 to a high of 0.83 (see Figure 6-3).

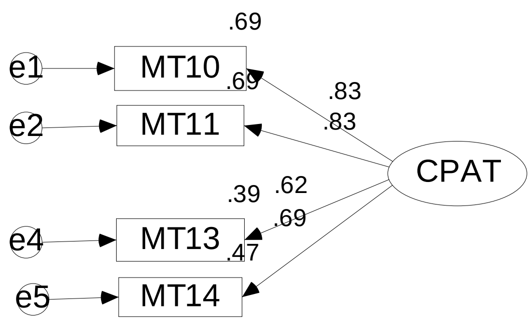


Figure 6-3: Congeneric model of system compatibility

	Estimate	S.E.	C.R.	P
T13 < --- CPAT	1.000			
T11 < --- CPAT	1.379	.179	7.715	***
T110 < --- CPAT	1.370	.189	7.248	***
T14 < --- CPAT	1.052	.160	6.559	***

*** = Significant at $p < 0.001$

Table 6-5: Regression weights of system compatibility construct

	Estimate	S.E.	C.R.	P
CPAT	.803	.206	3.899	***
eCPAT4	1.275	.168	7.605	***
eCPAT2	.698	.141	4.936	***
eCPAT1	.669	.137	4.872	***
eCPAT5	1.004	.139	7.211	***

Table 6-6: Variances of system compatibility construct

All the regression weights and variances shown in Table 6-5 and 6-6 were significant at level with $p < 0.001$.

6.5.1.4 Confirmation of the Top Management Support Construct

As shown in Figure 6-4, the one-factor congeneric model for top management support showed that the model fit the data well: χ^2 (chi-square) of 6.444, df = 5, and p value = 0.2651 (Bollen-Stine bootstrap p = 0.212). Moreover, other measures confirmed model fit as CMIN/df = 1.289, GFI = 0.984, AGFI = 0.951, TLI = 0.993, CFI = 0.996, and RMSEA = 0.044. All remaining items loaded highly on this factor, as factor loading ranged from a low of 0.70 to a high of 0.88 (see Figure 6-4).

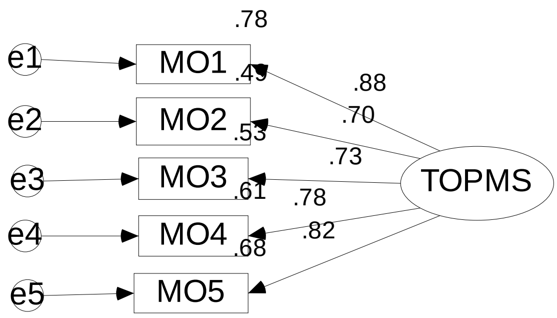


Figure 6-4: Congeneric model of top management support

	Estimate	S.E.	C.R.	P
O5 < --- TOPMS	1.000			
O4 < --- TOPMS	.889	.086	10.380	***
O3 < --- TOPMS	.808	.083	9.723	***
O2 < --- TOPMS	.857	.093	9.167	***
O1 < --- TOPMS	1.151	.092	12.471	***

*** = Significant at $p < 0.001$

Table 6-7: Regression weights of top management support construct

All the regression weights in Table 6-7 were significant at the level with $p < 0.001$.

6.5.1.5 Confirmation of the Organizational Size Construct

An examination the modification indices of the one-factor congeneric model for the construct of organizational size revealed that errors eOSIZE2 and eOSIZE4 might be correlated. Another method of re-specifying the model included covarying the error terms (Holmes-Smith, Cunningham & Coote 2006). Jöreskog & Sörbom (1996, p. 309) suggested this implies

"…when the correlation among the observed variables caused by the construct (organizational size) has been accounted for, there seems to be a correlation left between the

two items associated with these error terms (MO7 and MO9) that correlation can be interpreted as an indication that these questions (MO7 and MO9) correlate more than can be explained by organizational size".

In addition, correlating the error covariance approach has been suggested and used in many studies (e.g. Arbuckle & Wothe 1999; Baharim 2007; Byrne 2001; Schumacker & Lomax 2004). Correlating the error covariance approach is well justified both statistically and substantively (Byrne 2001). Thus, as shown in Figure 6-5 this model was re-specified by covarying the error terms by correlating eOSIZE2 and eOSIZE4 for achieving model fit.

According to Figure 6-5, correlating two error covariances, as suggested by the modification indices and re-specifying the model indicated a good model fit: χ^2 (chi-square) of 5.148, df = 4, *p* value = 0.272, Bollen-Stine bootstrap *p* = 0.331, CMIN/df = 1.287, GFI = 0.986, AGFI = 0.949, TLI = 0.988, CFI = 0.995, and RMSEA = 0.044. After the revised measurement model was tested with a new sample recommended by Thompson (2000), all remaining items loaded highly on this factor, as factor loading ranged from a low of 0.50 to a high of 0.84 (see Figure 6-5).

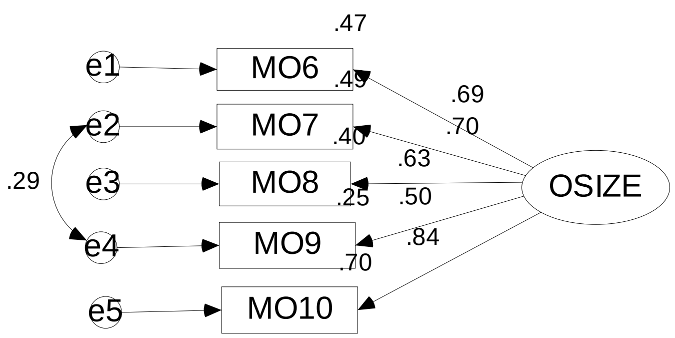


Figure 6-5: Congeneric model of organizational size

	Estimate	S.E.	C.R.	P
O8 < --- OSIZE	.719	.096	7.513	***
O7 < --- OSIZE	.821	.105	7.801	***
O6 < --- OSIZE	.877	.114	7.676	***
O9 < --- OSIZE	.674	.124	5.428	***
O10 < --- OSIZE	1.000			

*** = Significant at $p < 0.001$

Table 6-8: Regression weights of organizational size construct

	Estimate	S.E.	C.R.	P
eOSIZE2 < --- > eOSIZE4	.404	.117	3.454	***

Table 6-9: Covariances of organizational size construct

All the regression weights of the organizational size construct represented in the Table 6-8 were all significant with $p < 0.001$, as was the covariance of the organizational size construct. As discussed by Holmes-Smith, Cunningham & Coote (2006) above, the deletion or dropping of items cannot be applied because the model was shown a worse fit to the data. Thus, the covariance between eOSIZE2 and eOSIZE4 could not be deleted because it might affect the model so the researcher used the method of covarying the error terms for re-specifying the model suggested by Holmes-Smith, Cunningham & Coote (2006). Also OSIZE2 and Osize4 showed strong factor loadings (Hair et al. 2006). This model was re-specified by covarying the error terms by correlating eOSIZE2 and eOSIZE4 for achieving model fit.

6.5.1.6 Confirmation of the Absorptive Capacity Construct

The initial model for the one-factor congeneric model of absorptive capacity was found to show a poor fit of the model to the data. However, after respecifying the model as shown in Figure 6-6 by correlating two error covariances, the result indicated that the model fitted the data positively well: χ^2 (chi-square) of 4.498, df = 4, and p value = 0.343 (Bollen-Stine bootstrap p = 0.464). Moreover, other measures showed significant model fit as CMIN/df = 1.125, GFI = 0.988, AGFI = 0.955, TLI = 0.996, CFI = 0.998, and RMSEA = 0.029. After the revised measurement model was tested with a new sample recommended by Thompson (2000), all remaining items loaded highly on this factor, as factor loading ranged from a low of 0.61 to a high of 0.85 (see Figure 6-6).

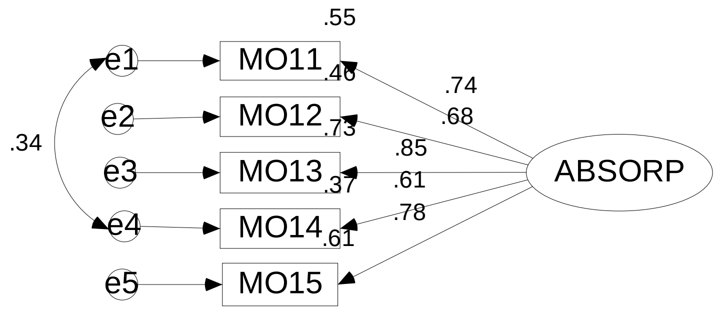


Figure 6-6: Congeneric model of absorptive capacity

	Estimate	S.E.	C.R.	P
O14 < --- ABSORP	1.000			
O13 < --- ABSORP	1.536	.206	7.442	***
O12 < --- ABSORP	1.151	.177	6.490	***
O11 < --- ABSORP	1.180	.144	8.407	***
O15 < --- ABSORP	1.239	.177	7.016	***

*** = Significant at $p < 0.001$

Table 6-10: Regression weights of absorptive capacity construct

	Estimate	S.E.	C.R.	P
eASORP4 < --- > eASORP1	.374	.118	3.180	.001

Table 6-11: Covariances of absorptive capacity construct

All values of the regression weights shown in Table 6-10 were significant with $p < 0.001$, while the value of the covariance as $p = 0.001$in Table 6-11 was a little high, but still acceptable at a significant level of 0.05. As Byrne (2001) states that correlating the error covariance approach can be justified both statistically and substantively, eASORP4 was correlated to eASORP1 to improve model fit. In addition, discussed by Holmes-Smith, Cunningham & Coote (2006) above, the deletion or dropping of items cannot be applied because the model was shown a worse fit to the data. Thus, the covariance between eASORP4 and eASORP1 could not be deleted as it might affect the model fit so the researcher used covarying the error terms for re-specifying the model suggested by (Holmes-Smith, Cunningham & Coote 2006). Also, ASORP4 and Asorp1 indicated strong factor loadings (Hair et al. 2006). This model was re-specified by covarying the error terms by correlating eSORP4 and eSORP1 for achieving model fit.

6.5.1.7 Confirmation of the Internal Need Construct

As shown in Figure 6-7, one-factor congeneric model of internal need construct produced a good fit of the model to the data after deleting the third item as it was found to be correlated and redundant with the fourth item: χ^2 (chi-square) of 3.978, df = 2, and p value = 0.137 (Bollen-Stine bootstrap $p = 0.146$). Moreover, other measures showed significant model fit as CMIN/df = 1.989, GFI = 0.987, AGFI = 0.937, TLI = 0.962, CFI = 0.987, and RMSEA = 0.081. As indicated by MacCallum, Browne & Sugawara (1996), RMSEA in the range of 0.05 to 0.10 was considered an indication of acceptable fit. Thus, RMSEA is a little bit high, but acceptable. After the revised measurement model was tested with a new sample recommended by Thompson (2000), all remaining items loaded highly on this factor, as factor loading ranged from a low of 0.49 to a high of 0.78 (see Figure 6-7).

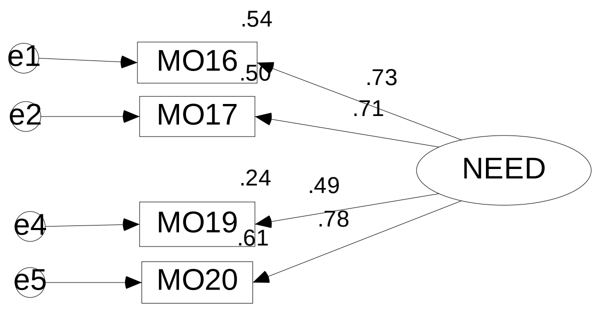


Figure 6-7: Congeneric model of internal need

	Estimate	S.E.	C.R.	P
O20 < --- NEED	1.000			
O19 < --- NEED	.658	.124	5.321	***
O18 < --- NEED	.988	.123	8.004	***
O17 < --- NEED	.932	.119	7.863	***
O16 < --- NEED	1.031	.122	8.477	***

*** = Significant at $p < 0.001$

Table 6-12: Regression weights of Internal need construct

	Estimate	S.E.	C.R.	P
NEED	1.322	.266	4.967	***
eNEED5	.833	.165	5.053	***
eNEED4	1.614	.205	7.865	***
eNEED2	1.102	.176	6.270	***
eNEED1	1.016	.171	5.950	***

Table 6-13: Variances of internal need construct

All the values of regression weights shown in Table 6-12 and variances in Table 6-13 were significant with $p < 0.001$.

6.5.1.8 Confirmation of the Competitive Pressure Construct

The congeneric model of the competitive pressure construct was tested. Initially, the model was found as a poor fit, but after re-specifying the model by correlating two error covariances, the final model as shown in Figure 6-8 had a very good fit to the data in statistics where: χ^2 (chi-square) of 4.821, df = 4, and *p* value = 0.369 (Bollen-Stine bootstrap *p* = 0.570). Moreover, other measures showed significant model fit as CMIN/df = 1.070, GFI = 0.989, AGFI = 0.960, TLI = 0.998, CFI = 0.999, and RMSEA = 0.029. After the revised measurement model was tested with a new sample recommended by Thompson (2000), all remaining items loaded highly on this factor, as factor loading ranged from a low of 0.66 to a high of 0.92 (see Figure 6-8).

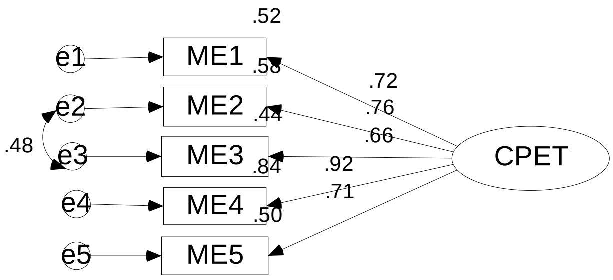


Figure 6-8: Congeneric model of competitive pressure

	Estimate	S.E.	C.R.	P
E4 < --- CPET	1.000			
E3 < --- CPET	.747	.088	8.464	***
E2 < --- CPET	.984	.093	10.627	***
E1 < --- CPET	.808	.080	10.050	***
E5 < --- CPET	.638	.065	9.852	***

*** = Significant at $p < 0.001$

Table 6-14: Regression weights of competitive pressure construct

	Estimate	S.E.	C.R.	P
eCPET3 < --- > eCPET2	.650	.157	4.147	***

Table 6-15: Covariance of competitive pressure construct

The Table 6-14 shows that the regression weights were significant at with $p < 0.001$. Moreover, the covariance between eCPET3 and eCPET2 in Table 6-15 was also significant with $p < 0.001$. As discussed by Holmes-Smith, Cunningham & Coote (2006) above, the deletion or dropping of items cannot be applied because the model was shown a worse fit to the data. The covariance between eCPET3 and eCPET2 could not be deleted as it would affect the model so the researcher used the method of covarying the error terms for re-specifying the model suggested by (Holmes-Smith, Cunningham & Coote 2006). Also CPET 3 and CPET2 showed strong factor loadings (Hair et al. 2006). Thus, this model was re-specified by covarying the error terms by correlating eCPET3 and eCPET2 for achieving model fit.

6.5.1.9 Confirmation of the Vendor Selection Construct

The initial one-factor congeneric model of vendor selection indicated a poor fit of the data to the model. However, as shown in Figure 6-9 when re-specifying the model by correlating two error covariances, the result indicated that the model fitted the data very well: χ^2 (chi-square) of 4.308, df = 4, and p value = 0.366 (Bollen-Stine bootstrap p = 0.437). Moreover, other measures showed significant model fit as CMIN/df = 1.077, GFI = 0.989, AGFI = 0.959, TLI = 0.998, CFI = 0.999, and RMSEA= 0.023. After the revised measurement model was tested with a new sample recommended by Thompson (2000), all remaining items loaded highly on this factor, as factor loading ranged from a low of 0.58 to a high of 0.90 (see Figure 6-9).

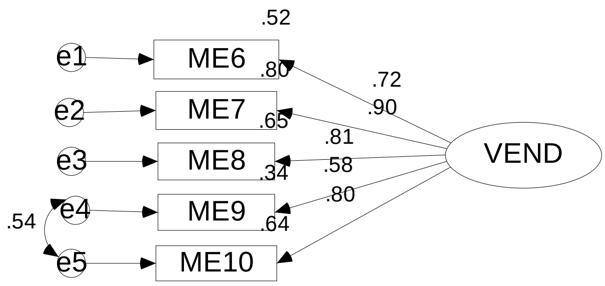


Figure 6-9: Congeneric model of vendor selection

	Estimate	S.E.	C.R.	P
E9 < --- VEND	1.000			
E8 < --- VEND	1.384	.192	7.192	***
E7 < --- VEND	1.492	.197	7.583	***
E6 < --- VEND	1.200	.180	6.652	***
E10 < --- VEND	1.379	.142	9.742	***

*** = Significant at $p < 0.001$

Table 6-16: Regression weights of vendor selection construct

	Estimate	S.E.	C.R.	P
eVEND4 < --- > eVEND5	.646	.133	4.867	***

Table 6-17: Covariances of vendor selection construct

All the values of regression weights and covariance represented in Tables 6-16 and 6-17 were all significant with p < 0.001. As discussed by Holmes-Smith, Cunningham & Coote (2006) above, the deletion or dropping of items cannot be applied because the model was shown a worse fit to the data. The covariance between eVEND4 and eVEND5 could not be deleted because it might affect the model fit so the researcher selected to apply the method covarying the error terms for re-specifying the model suggested by (Holmes-Smith, Cunningham & Coote 2006). Also VEND4 and VEND5 showed strong factor loadings (Hair et al. 2006). Thus, this model was re-specified by covarying the error terms by correlating eVEND4 and eVEND1 for achieving model fit.

6.5.1.10 Confirmation of the BIDSA Adoption Construct

The initial model for the one-factor congeneric model of BIDSA adoption was found to show poor fit of the model to the data: χ^2 (chi-square) of 13.755, df = 5, and *p* value = 0.017 (Bollen-Stine bootstrap *p* = 0.019). Other measures also showed the model unfitted as CMIN/df = 2.751, GFI = 0.967, AGFI = 0.902, TLI = 0.937, CFI = 0.968, and RMSEA = 0.108.

This model was re-specified by covarying the error term by correlating eADOPT4 and eAdopt5 for attempting to achieve model fit. As shown in Figure 6-10, the new model was then modified and found to have a good model fit to the data in statistics as follows: χ^2 (chi-square) of 7.051, df = 4, and *p* value = 0.133 (Bollen-Stine bootstrap *p* = 0.311). Moreover, other measures also showed significant model fit as CMIN/df = 1.763, GFI = 0.983, AGFI = 0.936, TLI= 0.973, CFI= 0.973, and RMSEA= 0.072. After the revised measurement model was tested with a new sample recommended by Thompson (2000), all remaining items loaded highly on this factor, as factor loading ranged from a low of 0.62 to a high of 0.86 (see Figure 6-10).

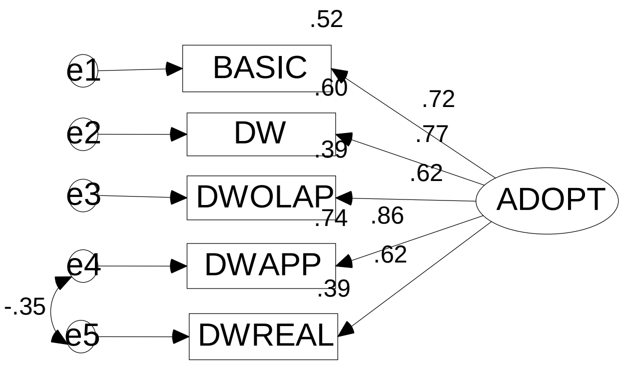


Figure 6-10: Congeneric model of BIDSA adoption

	Estimate	S.E.	C.R.	P
ADOPT4 < --- ADOPT	1.000			
ADOPT3 < --- ADOPT	.623	.084	7.408	***
ADOPT2 < --- ADOPT	.655	.066	9.966	***
ADOPT1 < --- ADOPT	.748	.080	9.335	***
ADOPT5 < --- ADOPT	.741	.108	6.838	***

*** = Significant at $p < 0.001$

Table 6-18: Regression weights of BIDSA adoption construct

	Estimate	S.E.	C.R.	P
eADOPT4 < --- > eADOPT5	-.370	.139	-2.667	.008

Table 6-19: Covariances of BIDSA adoption construct

All the values of regression weights represented in Table 6-18 were all significant with $p < 0.001$. Following this, Table 6-19 shows the covariance of the BIDSA adoption construct in which the value was significant at a level of 0.05. As Byrne (2001) states that correlating the error covariance approach can be justified both statistically and substantively, eADOPT4 was correlated to eADOPT5 to improve model fit. In addition, discussed by Holmes-Smith, Cunningham & Coote (2006) above, the deletion or dropping of items cannot be applied because the model was shown a worse fit to the data. Thus, the covariance between eADOPT4 and eADOPT5 could not be deleted because it might affect the model fit so the researcher applied the method covarying the error terms for re-specifying the model (Holmes-Smith, Cunningham & Coote 2006). The items of ADOPT4 or ADOPT5 could not be deleted as they showed strong factor loadings (Hair et al. 2006) and were important to the IT adoption as theorized in Chapter 3. Thus, this model was re-specified by covarying the error terms by correlating eADOPT4 and eADOPT5 for achieving model fit.

6.5.2 Discriminant Validity Using Confirmatory Factor Analysis (CFA)

The next step in the assessment of discriminant validity is confirmatory factor analysis (CFA). CFA is a technique requiring a prior specification of indicators or items (observed variables) to their respective latent variables (Jöreskog 1969). This technique is used to assess the measurement models by showing the goodness-of-fit to the data (Cunningham, E 2008). However, based on the research framework developed in Chapter 3, and using the results of the investigation of prior single-factor congeneric models, three measurement models are examined using CFA in analyzing discriminant validity.

In each round of validity analysis using CFA, there should be no more than five constructs under examination (Holmes-Smith, Cunningham & Coote 2006). In addition, as the proposed model comprises nine exogenous constructs and was divided into three groups as theorized in Chapter 3, the three measurement models are as follows:

1. The analysis using CFA of technological innovation factor model (BEN, CPLEX, CPAT)
2. The analysis using CFA of organizational factor model (TOPMS, OSIZE, ABSORP, NEED)

3. The analysis using CFA of environmental factor model (CPET, VEND).

The investigation of each of measurement models is presented below.

6.5.2.1 Analysis Using CFA of Technological Innovation Factor (TECH) Model

Using the results of the examination of the single-factor congeneric model, three latent variables are examined in the technological innovation model. There are fourteen items (TECH1-TECH14) in this specific exogenous latent constructs (factors). It is recommended to delete indicators from SEM analysis if the value of sample correlation between two indicators exceeds 0.8 because of multicollinearlity (Holmes-Smith, Cunningham & Coote 2006). After performing SEM analysis, no values of sample correlation between the two indicators exceeded 0.8 (see Appendix A8, Table A8-1) and therefore, no items were deleted to improve the model fit of the data. In addition, to provide appropriate validity analysis, it is important to investigate a standardized residual covariance between two indicators. This is the difference between the sample covariance and the model-implied covariance (Joreskog & Sorbom 1984). Most standardized residuals should have an absolute value less than 2 to present a correct model (Cunningham 2008).

In the analysis of the technological construct, the initial model of the technological construct indicated a poor fit of the data. As discussion above, there are two pairs of indicators that have absolute values of standardized residual covariance larger than 2. This is an indication that a particular covariance is not well reproduced by the hypothesized model (Cunningham 2008). Thus, some or all of the items should be dropped. After deleting the following additional four items (MT1, MT5, MT9, and MT10), the model does fit the data very well as absolute values of standardized residual covariance are not larger than 2 (see Appendix A8, Table A8-2). In addition, from all implied moments examination, the pattern and structure coefficients demonstrate that three constructs in the measurement model are empirically distinguishable. This is illustrated in Figure 6-11.

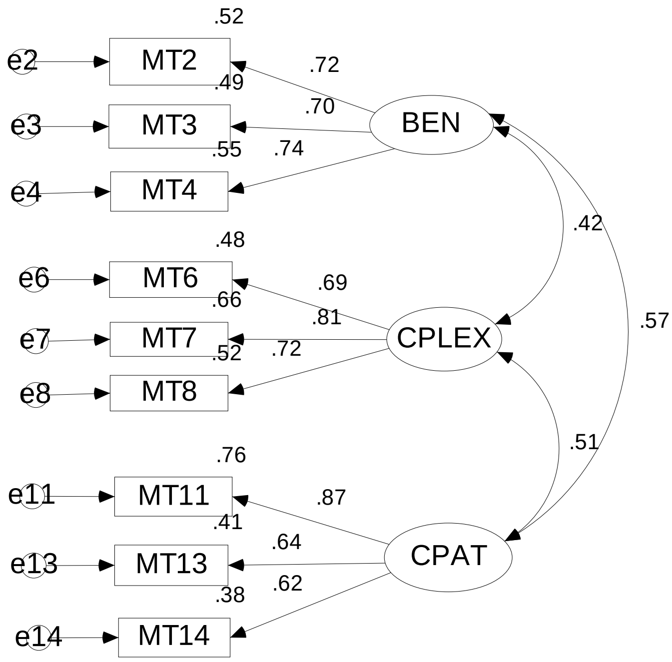


Figure 6-11: Measurement model of technological constructs

The modified model in Figure 6-11 yields χ^2 (chi-square) of 35.448, df = 24, and *p* value = 0.062 (Bollen-Stine bootstrap *p* = 0.219, which is not significant at the level of 0.05). This indicated that the model fits the data well. However, other alternatives should be provided to achieve a model fit (Mulaik 2007). Substantively, other measures showed significant model fit as CMIN/df = 1.477, GFI = 0.953, AGFI = 0.912, TLI = 0.959, CFI = 0.973, and RMSEA = 0.057 (see rationale in Table 6-2). Thus, it can be suggested that this model fits the data very well. All remaining items loaded highly on these factors as the factor loading range was from a low of 0.62 to a high of 0.87) (see Figure 6.11).

	Correlation Estimate
BEN < --- > CPEX	0.436
CPEX < --- > CPAT	0.496
BEN < --- > CPAT	0.543

Table 6-20: Correlations for three technological innovation constructs

According to Table 6-20, the three latent constructs are different because correlations between latent constructs are not greater than 0.8. Larger correlations between latent constructs (greater than 0.8) suggest a lack of discriminant validity (Cunningham 2008).

6.5.2.2 Analysis Using CFA of Organizational Factor (ORG) Model

There are twenty indicators (O1-O20) associated with this specific exogenous latent construct (factors). It is necessary to investigate multicollinearlity, but it was found that there was no sample correlation value between two indicators exceeding 0.8 (see Appendix A8, Table A8-3). Thus, this indicated that there was no multicollinearlity between the two indicators.

Initially, it can be acknowledged that the initial model of the organizational construct does not fit the data well. Thus, the model needs to be re-specified. After an examination of the standardized residual covariances, additional seven items comprising MO1, MO3, MO6, MO9, MO11, MO15, and MO20 (greater than 2) were deleted to obtain a good fit model. After deleting seven items, absolute values of standardized residual covariance are not larger than 2 (see Appendix A8, Table A8-4). The modified model is presented in Figure 6-12.

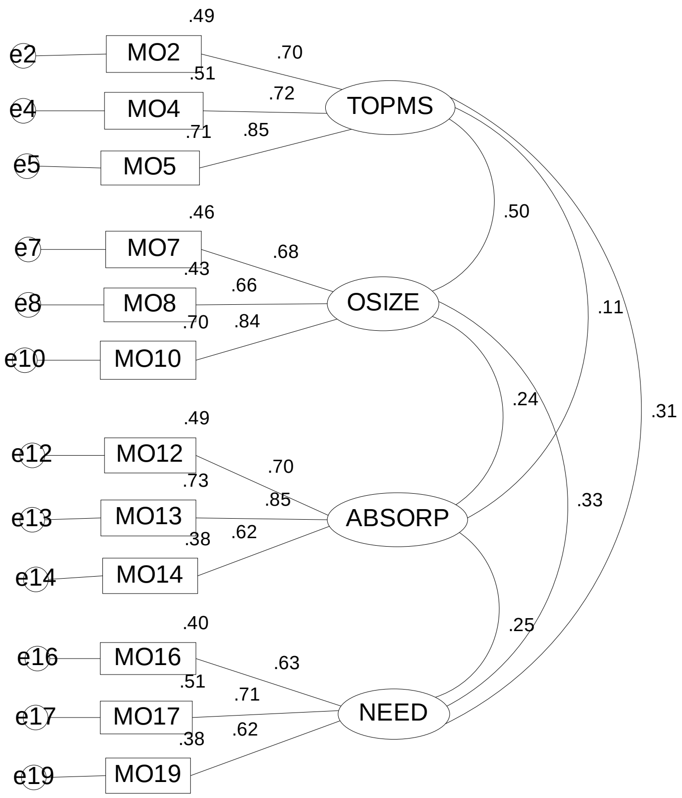


Figure 6-12: Measurement model of organizational constructs

From Figure 6-12, the pattern and structure coefficients indicated that four factors in the measurement models are empirically distinguishable. These indicated discriminant validity of the four factors in the model. The model in Figure 6-12 yields a chi-square (χ^2) of 76.671, degree of freedom = 48, and p value = 0.005 (Bollen-Stine *p* value = 0.053 which is not significant at the level of 0.05). Although it could be indicated that the model fits the data well, chi-square statistics are very sensitive to sample size. It is more appropriated to further alternatives at other fit measure for providing a model fit (Mulaik 2007). Fortunately, other fit measures indicated the goodness of fit of the model CMIN/df = 1.597, GFI = 0.922, AGFI = 0.874, TLI = 0.923, CFI = 0.944, and RMSEA = 0.063 (see rationale in Table 6-2). However, CFI shows the value (0.944) close to 0.950 which could be indicated as a good fit (Hu & Bentler 1999). All remaining items loaded highly on these factors as the factor loading range was from a low of 0.62 to a high of 0.85) (see Figure 6-12).

	Correlation Estimate
TOPMS < --- > OSIZE	0.503
ABSORP < --- > NEED	0.252
TOPMS < --- > NEED	0.311
OSIZE < --- > NEED	0.329
TOPMS < --- > ABSORP	0.107
OSIZE < --- > ABSORP	0.238

Table 6-21: Correlations for four organizational constructs

According to Table 6-21, the four latent constructs are different because correlations between latent constructs are not greater than 0.8. Larger correlations between latent constructs (greater than 0.8) suggest a lack of discriminant validity (Cunningham 2008).

6.5.2.3 Analysis Using CFA of Environmental Factor (ENV) Model

There are ten items (E1-E10) relating to the environmental constructs (factors). In the same way as in section 6.5.2.1 and 6.5.2.2, no problem was found about multicollinearlity between two indicators (see Appendix A8, Table A8-5). However, it was found that in the analysis of the environmental construct, the initial model of this construct indicated a poor fit of the data. After the examination of the standardized residual covariance, additional three items comprising ME1, ME3, and ME9 were deleted to get an improved fit model. The deletion process has to be done because those items have an absolute value of standardized residual covariance greater than 2. After deleting these items, absolute values of standardized residual covariance are not greater than 2 (see Appendix A8, Table A8-6). According to Cunningham (2008), this indicates that a particular covariance is not well reproduced by the hypothesized model. Thus, the new model is presented in Figure 6-13.

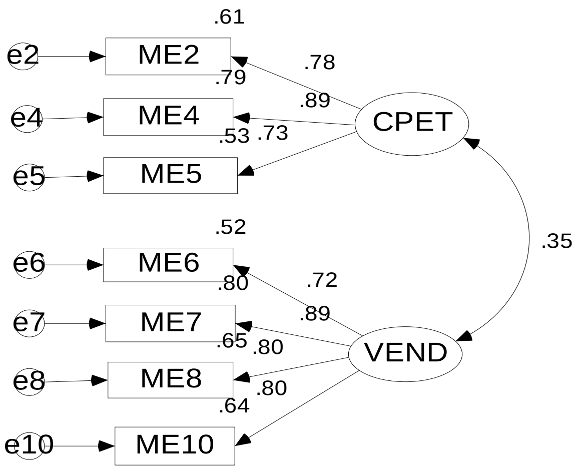


Figure 6-13: Measurement model of environmental constructs

From Figure 6-13, the pattern and structure coefficients indicated that two factors in the measurement models are empirically distinguishable. These indicated discriminant validity of the two factors in the model. The model in Figure 6-13 yields a chi-square (χ^2) of 14.494, degree of freedom = 13 and p value = 0.340 (Bollen-Stine *p* value = 0.470 which is not significant at the level of 0.05). However, chi-square statistics might be very sensitive to sample size. Alternatively, it is more appropriated to further look at other fit measure to indicate the model fit the data very well (Mulaik 2007). Other fit measures indicated the goodness of fit of the model CMIN/df = 1.115, GFI = 0.974, AGFI = 0.944, TLI = 0.995, CFI = 0.997, and RMSEA = 0.028 (see rationale in Table 6-2). It could be positively indicated that the model fits the data very well. All remaining items loaded highly on these factors as the factor loading range was from a low of 0.72 to a high of 0.89) (see Figure 6-13).

	Correlation Estimate
CPET < --- > VEND	0.392

Table 6-22: Correlations for two environmental constructs

According to Table 6-22, the two latent constructs shown above are different because correlations between latent constructs are not greater than 0.8. Larger correlations between latent constructs (greater than 0.8) suggest a lack of discriminant validity (Cunningham 2008).

After all constructs in the measurement model were validated and satisfactory fit accomplished (Hair et al. 2006; Kline 2005), a structural model can further be tested and presented as the main stage of the analysis. That means the assessment of single-factor congeneric model for each construct was examined along with the fit of measure of the model, the single-factor congeneric model was tested to measures a construct's unidimensionality. Furthermore, three measurement models (e.g. TECH, ORG, and ENV) were examined using the CFA. This analysis was used to assess the measurement models to provide their goodness-of-fit to the data. It is now ready to further perform the full structural equation modelling for hypothesis testing.

6.6 STRUCTURAL MODELS: Development Empirical Analysis of "BIDSA Adoption Modelling (BIAM)"

Structural modelling is an approach where "*the portion of the model that specifies how the latent variables are related to each other*" (Arbuckle 2005, p. 90) is used. The SEM basically combines path analysis and the measurement model. Path analysis examines the relationship between indicators (observed variables) of latent constructs, however SEM assesses the relationships among latent constructs (Cunningham 2008). In other words, the structural model can be used to specify which latent variables directly or indirectly influence the values of other latent variables in the model (Byrne 1999). In this research, the purpose of the structural model is to examine the relationships through the significant paths between the latent variables, and to test the underlying hypotheses in order to answer the research questions outlined in Chapter 1.

In SEM, the hypothesized or causal relationships can be presented by using path diagram. Based on the proposed model and using the measurement models, two main full structural models: the BIAM I model (see Figure 6-14); and the BIAM II model (see Figure 6-15) are constructs. In this thesis, the SEM diagram consists of the constructs as unobservable variables, measured variables (composite variables), measurement errors, and arrows connecting relationships between the variables. For instance, as shown in Figure 6-14 below, manifest variables including measured variables (composite variables) (e.g. BENX, CPLEXX, CPATX, TOPMSX, OSIZEX, ABSORPX, NEEDX, CPETX, and VENDX) are enclosed in rectangle shapes. The variables for errors representing (e) are enclosed in small circles to signify that they are variables unmeasured. The parameter (z) represents the residual errors in the structural model resulting from random error or systematic influences. The single-headed arrows in this diagram represent causal paths. For example, the arrow leading from BENCX (benefit factor) to BIDSA adoption (ADOPTION) in Figure 6-14 implies that the adoption of BIDSA depends on a benefit factor. Otherwise, the double-headed arrows represent correlations or covariances as seen in the relationship between relational factors including TECH, ORG, and ENG (see Figure 6-15).

However, an important requirement in linear regression is no correlation between error variables and other predictor variables. Predictor variables (independent variables) (e.g. BEN, CPLEX, CPAT, TOPMS, OSIZE, ABSORP, NEED, CPET, and VEND) (see Table 6-1) are referred to as exogenous. Another variable (dependent variable) is endogenous (e.g. adoption) (see Table 6-1). An endogenous variable has at least one single-headed path pointing to itself, whereas exogenous variables have only single-headed paths going out from them. Then, for providing model fit, the measurement errors could be possibly correlated to each other by the double-headed arrow (Byrne 2001). The model after testing and modification is positively called the “Business Intelligence Adoption Model” representing the abbreviation as BIAM through this research.

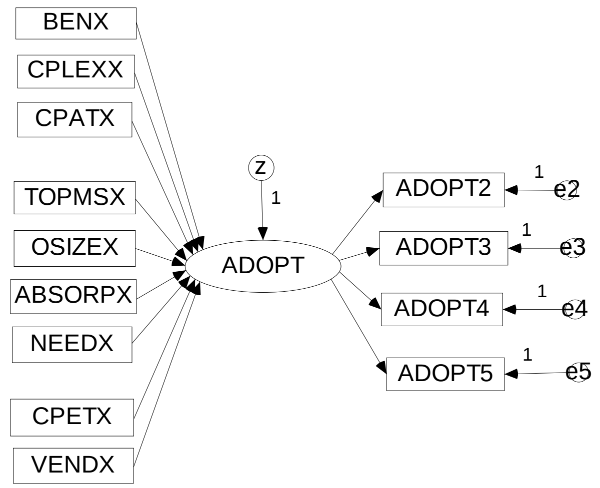


Figure 6-14: Proposed model of BIAM I

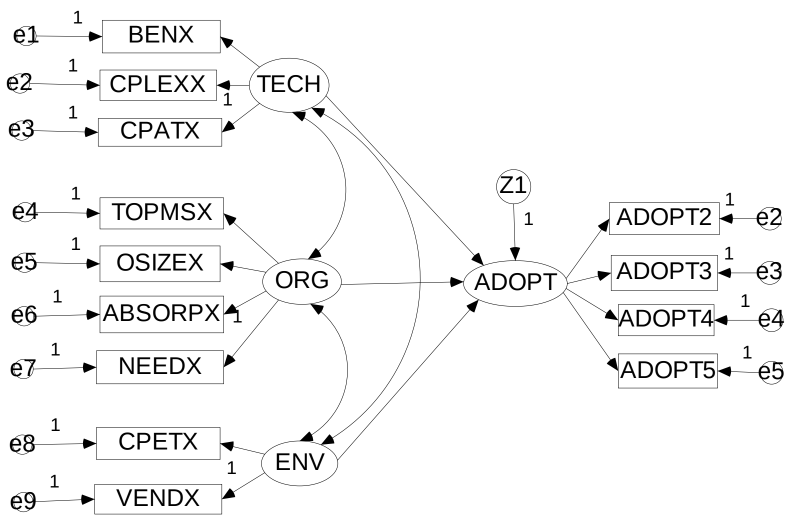


Figure 6-15: Proposed model of BIAM II

6.6.1 Developing the Composite Factor Model

Structural equation modelling requires variables to be normality distributed (Cunningham 2008; Hair et al. 2006). This issue is very important in performing SEM. The issue of the multivariate non-normality discussed in Chapter 4 and 5 showed that the results of multivariate normality in all variables were not shown to be multivariate normality (see Table 5-2). This could increase some problems when performing the full model in structural modelling using AMOS. Moreover, Bandalos (2002) suggested that using composite variables can help to reduce effects of non-normality. In addition, this can reduce the problem of small samples and improve the variables to sample size ratio (Bandalos & Finney 2001). In this case, the samples of this research are 150 which is more likely small for the number of returns required for a reliable model as previous literature suggested the appropriate samples of 200 or less (Barrett 2007). The use of composite factor model help to decrease the number of parameters to be estimated for a given model and smaller sample sizes may be more acceptable (Smith & Langfield-Smith 2004). Therefore, to avoid these issues a composite model technique was used to develop the structural model.

Given that the model of BIDSA adoption could be easier to continue testing, the researcher decided to perform this by applying a composite factor technique to deal with the model complexity. However, the composite factor measurement model also decreases the number of returns required for a reliable model (Hair et al. 2006). This can depict complex concepts in a single measure and reduce measurement error as well as make a valuable addition in any multivariate analysis. Composite variables are computed by integrating measured values from the component variables and replacing the latent construct with the composite variable

(Turner 2007). According to Hair et al. (2006), the latent variable in the model replaced by the composite variable is then regarded as a distinct manifest or measurement variable.

In addition, a composite factor model has been adopted as appropriate to the multivariate analysis in this study because of: 1) reducing the complexity of the model (Hair et al. 2006); 2) decreasing in the number of returns required for reliability (Holmes-Smith & Rowe 1994); 3) widely perceiving to use in many types of research (management and information systems) (e.g. Hair et al. 2006; Houghton et al. 2004; Raoprasert 2008; Turner 2007). This approach can improve reliability over individual items leading to less biased estimates of parameters and providing a model fit, while reducing effects of non-normality (Bandalos 2002; Holt 2004), and better use with small samples (Taylor, Celuch & Goodwin 2004).

One approach to compute a composite variable is to use simple average to calculate values (Hair et al. 2006). However, this method can be used when all items selected are showing with high factor loadings from factor analysis (Hair et al. 2006). After completing factor analysis using CFA (validity analysis using single-factor congeneric models and performing CFA) (see Figures from 6-1 to 6-10), it was found that no items selected have been found with low factor loadings (most of them were higher than 0.5). Hair et al. (2006) suggested that the standardized factor loadings should be higher than the recommended level of 0.5, however a level of reasonable magnitude above 0.4 is acceptable (Cunningham 2008).

However, this method does not consider the different factor loadings of each variable (Holmes-Smith & Rowe 1994). These researchers recommended a better approach in which a weighted average technique is taken into account for the factor loadings of each constituent. This indicated that standardized parameter estimates for these measures were deemed to be statistically significant ($p < 0.001$), providing unidimensional scales for each of nine factors. This approach is not influenced by any weaker loading factors having positive bias. In this thesis, the approach used to compute composite variables is adopted from Turner (2007).

The formula utilizing these composite variables used in this thesis is based on the following equation.

$$\textbf{Composite} = \left(\sum Fi\ Si\right) \div \left(\sum Fi\right)$$

Si : The item score (S) (Score rating from 1-7)

Fi : The value of factor (F) loadings

To create these composite variables, involves combining scores of two or more items on a unidimensional scale. Factors from Figure 6-14 and Figure 6-15 (e.g. benefit (BEN); task complexity (CPLEX), system compatibility (CPAT), top management support (TOPMS), organizational size (OSIZE), absorptive capacity (ABSORP), internal need (NEED), competitive intensity (CPET), and vendor selection (VEND) as well as BIDSA adoption (ADOPT) were used to compute composite variables in developing and testing the structural model. The method of this calculation is outlined as follows:

Factor Name	Components (Items)	Examples of Composite Variable Calculation	Composite Variables
BEN	T2, T3, T4	((FT2*ST2)+(FT3*ST3)+(FT4*ST4))/ (FT2+FT3+FT4)	(T2, T3, T4) = BENCx
CPLEX	T6,T7, T8	…	(T6,T7, T8) =CPLEXCx
CPAT	T11, T13, T14	…	(T11, T13, T14) = CPATCx
TOPMS	O2, O4, O5	…	(O2, O4, O5) = TOPMSCx
OSIZE	O7, O8, O10	…	(O7, O8, O10) = OSIZECx
ABSORP	O12, O13, O14	…	(O12, O13, O14) =ABSORPCx
NEED	O16, O17, O19	…	(O16, O17, O19) = NEEDCx
CPET	E2, E4, E5	…	(E2, E4, E5) = CPETCx
VEND	E6, E7, E8, E10	…	(E6, E7, E8, E10) =VENDCx
ADOPT	A1, A2, A3, A4, A5	((FA1*SA1)+(FA2*SA2)+(FA3*SA3)+(FA4*SA4)+(FA5*SA5))/ (FA1+FA2+FA3+FA4+FA5)	(A1, A2, A3, A4, A5) = ADOPTCx

FT: Factor loading values of technological variable
FO: Factor loading values of organizational variable
FE: Factor loading values of environmental variable
FA: Factor loading values of adoption variable
ST: Score values of technological variable
SO: Score values of organizational variable
SE: Score values of environmental variable
SA: Score values of adoption variable

Table 6-23: Structure and calculation method of composite variables

After performing the composite factor model, the latent constructs were replaced by composite variables which were determined by computations integrating measured values from the constituent variables. Therefore, all composite variables shown in Table 6-23: BENCx, CPLEXCx, CPATCx, TOPMSCx, OSIZECx, ABSORPCx, NEEDCx, CPETCx, VENDCx, and ADOPTCx were applied for the development of the BIDSA adoption model.

6.6.2 Developing the Structural Model of BIAM

Once every construct in the measurement model (stage one) was validated and satisfactory fit achieved, then the structural model can be tested and presented to provide the analysis (stage two). The SEM technique is useful for applying multiple indicators for the latent variables under investigation and the purpose was to examine relationships through determining the significant paths the latent variables. As suggested by Hair et al. (2006); (Holmes-Smith & Rowe (1994); and Turner (2007), an additional technique: the composite factor model, was conducted to reduce the complexity and increase more reliability of the proposed model. In addition, once composite variable were achieved, two new structural models of BIDSA adoption (BIAM I and BIAM II) were accomplished and presented in the flowing figures (Figure 6-16 and 6-17).

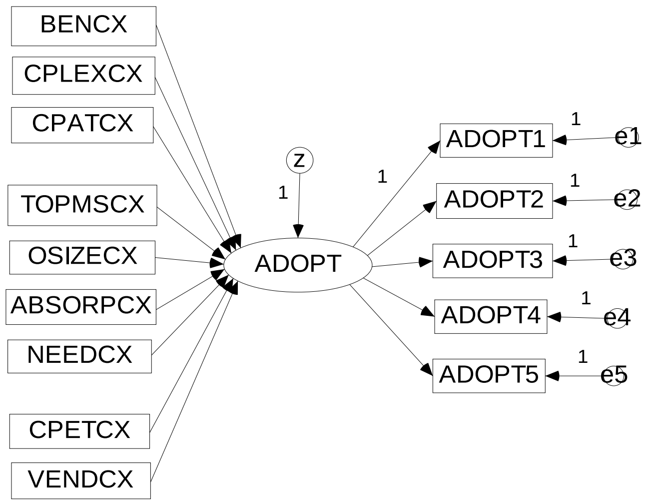


Figure 6-16: A Composite model of BIAM I

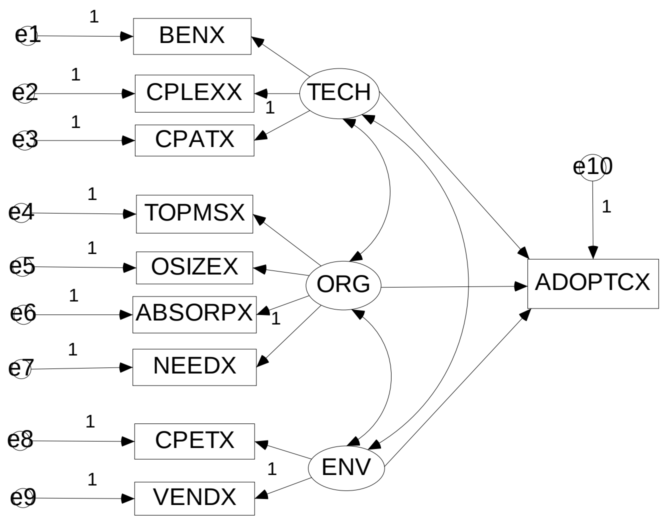


Figure 6-17: A Composite model of BIAM II

As the structural model can explain the relationships between the latent constructs (Byrne 1999), the causal relationships among the latent constructs can be investigated (Cunningham 2008; Hair et al. 2006). In the theoretical model proposed in Chapter 3, the underlying constructs were considered for two classes: 1) exogenous constructs (TECH: BENCx, CPLEXCx, and CPATCx; ORG: TOPMSCx, OSIZECx, ABSORPCx, NEEDCx; and ENVCx: CPETCx and VENDCx); and 2) endogenous construct (ADOPTCx). Thus, the structural model in this research can be used to test underlying hypotheses. These main hypotheses were presented in three main causal paths (H2, H3, H4) to determine the relationships between constructs.

Hypotheses Number	Hypotheses Description
H2: TECH ---> ADOPT	Technological innovation factors will positively affect BIDSA adoption
H2a: BEN ---> ADOPT	Benefit will positively affect a technological factor for BIDSA adoption
H2b: CPLEX ---> ADOPT	Task complexity will positively affect a technological factor for BIDSA adoption
H2c: CPAT ---> ADOPT	System Compatibility will positively affect a technological factor for BIDSA adoption
H3: ORG ---> ADOPT	Organizational factors will positively affect BIDSA adoption
H3a: TOPMS ---> ADOPT	Top management support will positively affect an organizational factor for BIDSA adoption
H3b: OSIZE ---> ADOPT	Organizational size will positively affect an organizational factor for BIDSA adoption
H3c: ABSORP ---> ADOPT	Absorptive capacity will positively affect an organizational factor for BIDSA adoption
H3d: NEED ---> ADOPT	Internal need will positively affect an organizational factor for BIDSA adoption
H4: ENV ---> ADOPT	Environmental factors will positively affect BIDSA adoption
H4a: CPET ---> ADOPT	Competitors will positively affect an environmental for BIDSA adoption
H4b: VEND ---> ADOPT	Vendor selection will positively affect an environmental for BIDSA adoption
H5: INOVATION ---> ADOPT	Any innovation factor will positively affect BIDSA adoption.

Table 6-24: Underlying hypotheses of the research

A structural model represents the relationships between constructs (Hair et al. 2006). If the measurement model does fit well and sufficiently valid, it can be transformed into a full structural model using theoretical basis. In order to evaluate the structural model, goodness-of-fit indices are applied to assess the results of the hypothesized structural model fit the data. However, many researchers suggest that it is necessary to re-specify the model until the model is achieved coming with acceptable statistical fit and indicating a theoretically meaningful representation of the observed data (Anderson, JC & Gerbing 1988; Hair et al. 2006; Kline 2005). In the AMOS program, this can be done by examining the standardized residual covariance matrix (SRMC) and Modification Indices (M.I.) (Cunningham 2008).

6.6.2.1 Model Estimation

After the assumptions underlying structural equation modelling were completed, the coefficient parameter estimates were examined along with the model fit indices to test hypotheses H2, H3, H4, and H5. According to Garson (2008), standardized estimates are employed when research is performed comparing the importance of predictor variables within a single sample. Thus, standardized structural (path) coefficient estimates were used. According to Tabachnick & Fidell (2001), the parameter values are fundamental to SEM analysis and these were used to provide the estimated population covariance matrix for the model. These coefficient's values show significantly when the Critical Ratio (C.R.) is greater than 1.96 for a regression weight (or standardized estimates) that the parameter is statically significant at the 0.05 levels. In other words, if C.R. does not exceed a value of 1.96 as the requirement, the regression weight of predictors in the prediction of relationships at the $p < 0.05$ level is not showing significantly different from zero. The regression weight represents the influence of one or more variables on another variable (Byrne 2001). In addition, by showing in the path analysis, the values for the paths linking constructs with a single-headed arrow represent standardized regression weights. The values next to the double-headed arrows represent correlations. Correlations are necessary for assumptions in SEM because the exogenous constructs (factors) are assumed to be correlated (Kline 2005).

6.6.2.2 Squared Multiple Correlations (SMC)

Fit measures provide information about how well the model fits the data, however these cannot provide any information about the strength of the structural paths in the model. Thus, this strength of the structural path is determined by using square multiple correlations (SMC). SMC refers to the values indicating the proportion of variance that is explained by the predictors of the variable in question (Byrne 2001). A measurement perspective represents how well an item measures a construct (Hair et al. 2006). Simple regression uses a single predictor of the dependent variable, whereas multiple regression uses two or more predictors (Hayduk 1987). It is important for this research to consider the SMC of each dependent variable together with fit measures for best describing the structural model (Arbuckle 2006). The interpretation of SMC is analogous to the $\boldsymbol{R^2}$ statistic in multiple regression analysis (Sharma 1996). There are no values of $\boldsymbol{R^2}$ that can be considered as a good or poor fit in all situations, because it depends on each particular situation and the nature of the available data (Jain 1994). However, SMC is also a useful statistics that is also independent of all units of measurement (Arbuckle 2006).

6.6.2.3 A Full Structural Model (The Hypothesized Model)

Based on the proposed model and using the measurement models, the analyses of the hypothesized structural model were conducted by testing the hypothesized model. In SEM, with a full structural model, the causal relationships among latent constructs can be investigated (Hair et al 2006; Byrne 2001). The specified causal relationships are shown in Table 6-24. In order to answer hypotheses H2, H3, H4, and H5 the two models of BIAM were tested. The first model of BIDSA Adoption (BIAM I) was designed to test hypotheses H2xi, H3xi, and H4xi (Xi represents a number of sub hypotheses). In addition, the second model of BIDSA adoption (BIAM II) was approached to provide solutions for hypotheses H2, H3, H4, and H5.

After the first model tested, the result showed that the model did not fit the data: χ^2 (chi-square) of 320.89, df= 77, *p* value = 0.000 (Bollen-Stine bootstrap *p*= 0.007), CMIN/df=

4.167, GFI= 0.680, AGFI= 0.563, TLI= 0.486, CFI= 0.565, and RMSEA= 0.146 (see Figure 6-18). Thus, modifications were required for the model to improve the fit (Byrne 2001; Kline 2005).

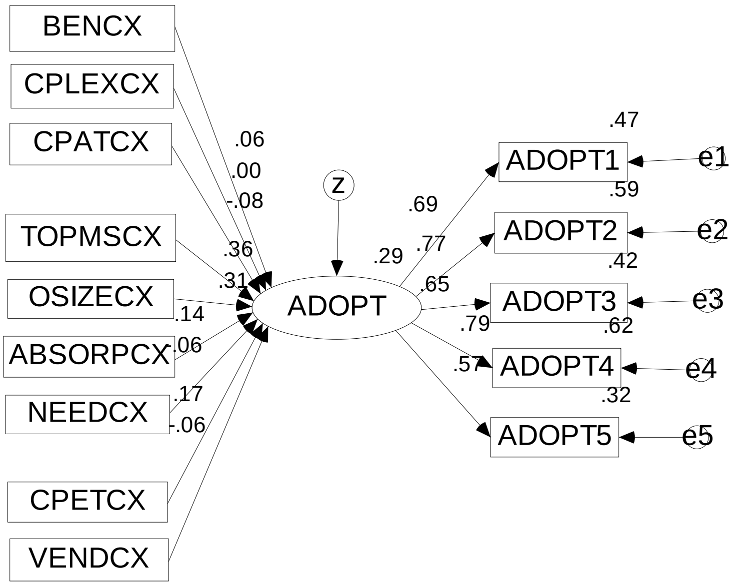


Figure 6-18: Initial model of BIDSA adoption (BIAM I)

In AMOS, the modification indices (M.I.) indicated that the latent variables of BENCX, CPLEXCX, CPATCX, TOPMSCX, OSIZECX, ABSORPCX, NEEDCX, CPETCX, and VENDCX were required to be related (correlated). Two error covariances also needed to be correlated to improve fit of the model to the data (see Figure 6-19). After testing the model again, it still had poor fit. However, the modification indices suggested that some exogenous variables had directly influenced the endogenous variables. For example, CPLEXCX had a direct influence on ADOPT 4 (in early adoption stage). Moreover, CPATCX showed a direct influence on ADOPT 5 (in early adoption stage). Last, CPETCX had a direct influence on ADOPT 3 (in early adoption stage). However, CPLEXCX (task complexity), CPATCX (system compatibility), and CPETCX (competitive pressure) have direct effects on adoption of 4, 5, and 3 at levels 0.05 respectively.

Thus, the model was modified again with direct influences by connecting exogenous variables to endogenous variables and showed a good fit of the data to the model: χ^2 (chi-square) of 109.89, df = 60, and *p* value = 0.000 (Bollen-Stine bootstrap *p*= 0.013). However, chi-square statistics is very sensitive to sample fluctuation. It is more appropriated to further look at other fit measure (Mulaik 2007). Fortunately, other fit measures indicated the goodness of fit of the model CMIN/df= 1.832, GFI= 0.901, AGFI= 0.827, TLI= 0.865, CFI= 0.911, and RMSEA= 0.075 (see rationale in Table 6-2). According to Blunch (2008), CFI-indices above 0.8 indicate "no problem of good fit" to the model. In addition, CFI shows the value (0.911) close to 0.950 which could be indicated as a good fit to the model (Hu & Bentler 1999). Therefore, after the revised measurement model was tested with a new sample recommended by Thompson (2000), the model of BIDSA adoption produced a good fit of the data to the model after showing directive paths and correlating covariances were drawn. The results of model estimations were presented in Table 6-25 to 6-29 below.

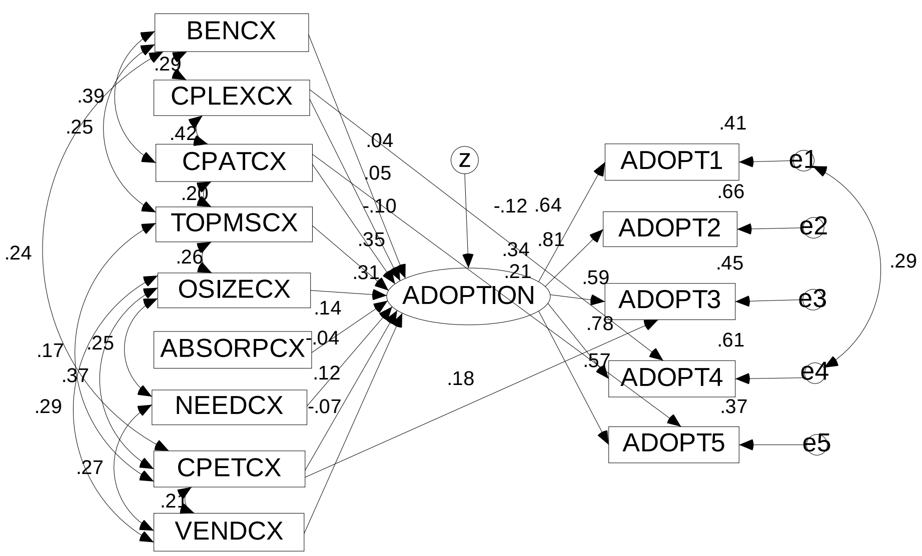


Figure 6-19: Final model of BIDSA adoption (BIAM I)

	Estimate	S.E.	C.R.	P
ADOPTION < --- BENCX	.047	.095	.501	.616
ADOPTION < --- CPLEXCX	.052	.090	.584	.559
ADOPTION < --- CPATCX	-.109	.096	-1.138	.255
ADOPTION < --- TOPMSCX	**.339**	**.088**	**3.865**	*****
ADOPTION < --- OSIZECX	**.350**	**.109**	**3.207**	**.001****
ADOPTION < --- ABSORPCX	.132	.073	1.796	.073
ADOPTION < --- CPETCX	.106	.078	1.356	.175
ADOPTION < --- VENDCX	-.061	.076	-.806	.420
ADOPTION < --- NEEDCX	-.045	.096	-.474	.636
ADOPT 1 < --- ADOPTION	1.000			
ADOPT 2 < --- ADOPTION	1.030	.142	7.268	***
ADOPT 3 < --- ADOPTION	.888	.148	5.991	***
ADOPT 4 < --- ADOPTION	1.350	.154	8.766	***
ADOPT 5 < --- ADOPTION	.998	.170	5.853	***
ADOPT 5 < --- CPATCX	**.392**	**.128**	**3.072**	**.002****
ADOPT 4 < --- CPLEXCX	**-.214**	**.098**	**-2.169**	**.030****
ADOPT 3 < --- CPETCX	**.241**	**.091**	**2.66**	**.008****

*** = value is statistically significant at the 0.001 level (two-tailed)

** = value is statistically significant at the 0.05 level (two-tailed)

Table 6-25: Regression weights of the model of BIDSA adoption (BIAM I)

Five research hypotheses between predictors and dependent variables in the BIAM I model are accepted. These are: H2b; H2c; H3; H3a; H3b; and H4a, while the rest are rejected. This suggested that TOPMS and OSIZE ----> ADOPT and CPET, CPLEX, and CPAT ----> ADOPT3, ADOPT4, and ADOPT5 respectively. It can be stated that top management support and organizational size significantly influenced BIDSA adoption. Concurrently, it was also found that only competitive pressure, task complexity, and system compatibility influenced BIDSA adoption at the early stage of adoption (early adopters) as theorized in Chapter 2, the rest are not statistically significant.

	Estimate	S.E.	C.R.	P
BENCX < --- > CPATCX	.296	.064	4.590	***
CPLEXCX < --- > CPATCX	.335	.070	4.808	***
OSIZECX < --- > CPETCX	.314	.070	4.502	***
BENCX < --- > CPETCX	.218	.065	3.348	***
TOPMSCX < --- > OSIZECX	.203	.060	3.407	***
BENCX < --- > CPLEXCX	.230	.064	3.618	***
OSIZECX < --- > VENDC	.238	.067	3.577	***
VENDCX < --- > NEEDCX	.213	.066	3.236	.001

TOPMSCX < --- > CPETCX	.176	.079	2.215	.027
BENCX < --- > TOPMSCX	.211	.065	3.229	.001
CPATCX < --- > TOPMSCX	.169	.062	2.733	.006
OSIZECX < --- > NEEDCX	.155	.048	3.224	.001
CPETCX < --- > VENDCX	.227	.083	2.748	.006
E1 < --- > E4	.321	.134	2.395	.017

Table 6-26: Covariances of the model of BIDSA adoption (BIAM I)

All covariances (first seven items) of the model of BIAM I in Table 6-26 were significant at level of 0.001. However, the *p* value of the other covariances in this table were a little high, but still acceptable at the level 0.05. This indicates that the constructs and error measurements mentioned in Table 6-26 need to be correlated.

	Estimate	S.E.	C.R.	P
BENCX	.759	.087	8.775	***
CPLEXCX	.825	.096	8.631	***
CPATCX	.772	.089	8.698	***
TOPMSCX	.930	.107	8.695	***
OSIZECX	.654	.074	8.773	***
ABSORPCX	.956	.111	8.631	***
CPETCX	1.106	.127	8.736	***
VENDCX	1.026	.118	8.662	***
NEEDCX	.613	.071	8.631	***
Z	.564	.148	3.822	***
E1	1.226	.171	7.163	***
E2	.463	.088	5.275	***
E3	1.048	.139	7.558	***
E4	1.002	.172	5.828	***
E5	1.667	.214	7.800	***

Table 6-27: Variances of the model of BIDSA adoption (BIAM I)

All the variances in Table 6-27 were significant at level 0.001.

	Estimate
ADOPT1	.411
ADOPT2	.662
ADOPT3	.451
ADOPT4	.613
ADOPT5	.369

Table 6-28: Squared multiple correlation (SMC) (BIAM I)

It also indicated that there are varying explanations for the dependent variables (see Table 6-28). The square multiple correlation (SMC) of a variable is the proportion of its variance that is accounted for by its predictors (Arbuckle 2006). Predictors (BEN, CPLEX, CPAT, TOPMS, OSIZE, ABSORP, NEED, CPET, and VEND) account for the variance of dependent variables, with a high explanation for ADOPT4 and ADOPT2 and a reasonable explanation for ADOPT1, ADOPT3, and ADOPT5. Specifically, the determinants account for:

- 66.2% of the variance of ADOPT2
- 61.3% of the variance of ADOPT4
- 45.1% of the variance of ADOPT3
- 41.1% of the variance of ADOPT1
- 36.9% of the variance of ADOPT5

In addition, the standardized regression weights are used since these allow the researcher to compare directly the relative effect of each independent variable on the dependent variable (Hair et al. 2006) (see Table 6-29).

	Estimate
ADOPTION < --- BEN	.045
ADOPTION < --- CPLEX	.051
ADOPTION < --- CPAT	-.104
ADOPTION < --- TOPMS	**.353**
ADOPTION < --- OSIZE	**.306**
ADOPTION < --- ABSORP	.139
ADOPTION < --- CPET	.121
ADOPTION < --- VEND	-.067
ADOPTION < --- NEED	-.038
ADOPT 5 < --- CPATCX	**.212**
ADOPT 4 < --- CPLEXCX	**-.121**
ADOPT 3 < --- CPETCX	**.183**

Table 6-29: Standardized regression weights for BIAM I

The relative affect (standardized regression weights) between factors and BIDSA adoption (ADOPT) shows stronger paths (with statistical significance) between TOPMS and ADOPT (0.353), OSIZE and ADOPT (0.306), CPET and ADOPT3 (0.183), CPLEX and ADOPT4 (-0.121), and CPAT and ADOPT5 (0.212). The rest are rather weaker with non statistical significance (see Table 6-29).

This could suggest that the higher level of top management support and organizational size toward using BIDSA by organizations, the greater the extent of the BIDSA usage in adoption and implementation. Moreover, this also suggests that the higher level of competitive pressure, task complexity, and system compatibility of users toward using BIDSA, the greater the extent of the BIDSA usage in the early adoption stage. In addition, the higher the level of BIDSA usage in adoption with the early adoption stage, the greater the extent of intention to use the BIDSA in the future.

From the model of BIAM I, it has been empirically and theoretically found that the best parsimonious model was achieved with some modifications Kline (2005). The structural model was therefore accepted as the final model. However, on a theoretical basis, the final model is consistent with a previous study in technological innovation adoption particularly relating to BIDSA technology, which has found that the technology/innovation factors, organizational factors, and environmental factors have been related to the innovation adoption model (Rogers 1995; Thong 1999; Tornatsky & Klien 1982; Tornatzky & Fleischer 1990).

Next, the second structural model of BIDSA adoption was performed to hypothesize hypotheses H2, H3, H4, and H5. After the second model (BIAM II) was tested (see Figure 6-

20), the result showed that the model seem not to show a good fit to the data because of chi-square: χ^2 (chi-square) of 48.427, df= 30, *p* value = 0.018 (Bollen-Stine bootstrap *p*= 0.066 which is not significant at the level of 0.05). However, chi-square statistics are very sensitive to sample size (Bagozzi & Yi 1988; Hair et al. 1998). It is more appropriated to further alternatives at other fit measure for providing a model fit (Mulaik 2007). Fortunately, other fit measures indicated the goodness of fit of the model: CMIN/df= 1.614, GFI= 0.941, AGFI= 0.891, TLI= 0.908, CFI= 0.939, and RMSEA= 0.064 (see rationale in Table 6-2). It is consistent with the work by Blunch (2008) that CFI-indices above 0.8 indicate "no problem of good fit" to the model. In addition, CFI shows the value (0.939) close to 0.950 which could be indicated as a good fit to the model (Hu & Bentler 1999). Modifications were not required for the model to improve the fit (Byrne 2001; Kline 2005). Thus, it could be positively indicated that the model fits the data very well.

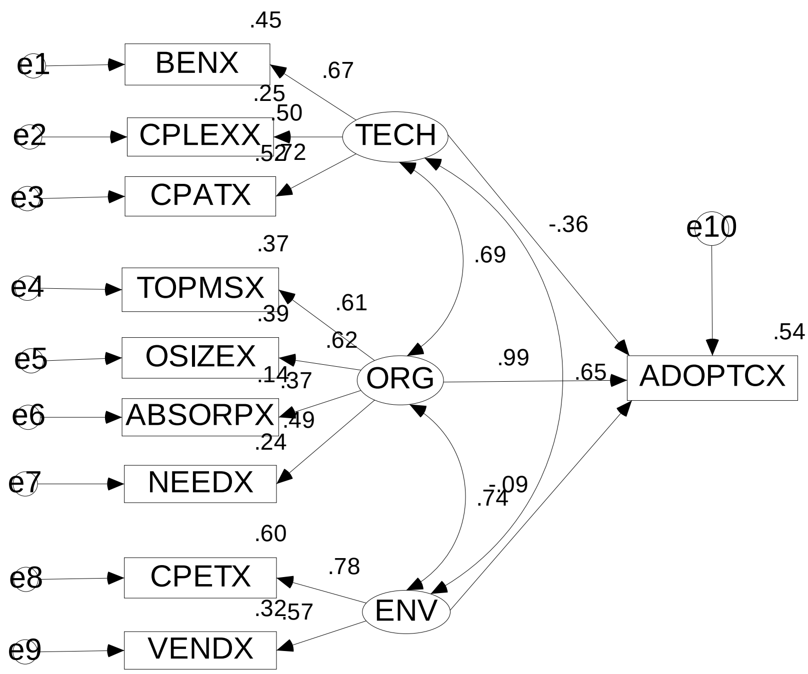


Figure 6-20: Initial and final model of BIDSA adoption (BIAM II)

Notes for Model:

Computation of degrees of freedom

Number of distinct sample moments	55
Number of distinct parameters to be estimated	25
Degree of freedom (55-25)	30

Results

Minimum was achieved

Chi-square	48.42
Degree of freedom	30
p value	0.18

These results also demonstrate that this structural model is the best fit. In addition, other results of model estimations were presented in Table 6-30 to 6-33 below.

	Estimate	**S.E.**	**C.R.**	**P**
CPATX < --- TECH	1.000			
CPLEXX < --- TECH	.712	.146	4.883	***
BENX < --- TECH	.946	.160	5.903	***
NEEDX < --- ORG	1.000			
ABSORPX < --- ORG	.789	.221	3.570	***
OSIZEX < --- ORG	1.238	.250	4.946	***
TOPMSX < --- ORG	1.346	.275	4.894	***
VENDX < --- ENV	1.000			
CPETX < --- ENV	1.335	.269	4.958	***
ADOPTX < --- ENV	-.133	.351	-.378	.705
ADOPTX < --- TECH	-.458	.270	-1.698	.089
ADOPTX < --- ORG	**2.008**	**.676**	**2.970**	**.003****

*** = value is statistically significant at the 0.001 level (two-tailed)

** = value is statistically significant at the 0.05 level (two-tailed)

Table 6-30: Regression weights of the model of BIDSA adoption (BIAM II)

	Estimate	S.E.	C.R.	P
ORG < --- > ENV	.314	.090	3.505	***
TECH < --- > ORG	.343	.089	3.854	***
TECH < --- > ENV	.435	.166	3.746	***

Table 6-31: Covariances of the model of BIDSA adoption (BIAM II)

All the covariances of the model of BIAM II in Table 6-31 were significant at a level of 0.001.

	Estimate	S.E.	C.R.	P
TECH	.782	.190	4.120	***
ORG	.317	.110	2.873	.004
ENV	.575	.183	3.152	.002
e3	.733	.140	5.230	***
e2	1.170	.154	7.593	***
e1	.842	.141	5.958	***
e7	.978	.124	7.900	***
e6	1.207	.146	8.278	***
e5	.766	.108	7.068	***
e4	.968	.135	7.168	***
e9	1.195	.172	6.948	***
e8	.672	.198	3.393	***
e10	.591	.174	3.395	***

Table 6-32: Variances of the model of BIDSA adoption (BIAM II)

Most of the variances in Table 6-32 were significant at level 0.001, except the variances of ORG and ENV which was significant at level 0.05.

	Estimate
ADOPT < --- TECH	-.088
ADOPT < --- ORG	.993
ADOPT < --- ENV	-.356

Table 6-33: Standardized regression weights (BIAM II)

In addition, the relative effect (standardized regression weights) between independent and dependent variables shows stronger paths (with statistical significance) between ORG and ADOPT (.993). The others (between TECH and ADOPT, and ENV and ADOPT) are rather weaker with non-statistical significance (see Table 6-33). These allow the researcher to compare directly the relative effect of each independent variable on the dependent variable (Hair et al. 2006). This may suggest that the higher level of organizational factors supported in developing BIDSA, the greater the extent of the BIDSA usage in adoption and implementation.

From the model of BIAM II, it has been empirically and theoretically found that the best parsimonious model was achieved without any modifications (Kline 2005). The structural model was therefore accepted as the final model. However, on a theoretical basis, the final model is consistent with a previous study in technological innovation adoption particularly relating to BIDSA technology, which has found that the technology/innovation factors, organizational factors, and environmental factors have been related to the innovation adoption model (Hwang et al. 2004; Ramamurthy, Sen & Sinha 2008).

6.7 RESEARCH HYPOTHESES (H1-H5) AND QUESTIONS (Q1-Q5)

In this research, the results of hypotheses testing for answering each research question as major findings are presented.

6.7.1 Hypotheses (H1)

In this section, the question below can be answered by testing H1.

Research Question I: "*How do the company characteristics differ in the extent of adoption and implementation of BIDSA by Australian organizations?*"

Hypothesis (H1): The stages of adoptions differ in the extent to which they use BIDSA in term of size of companies, industry types, and duration in using BIDSA

This research question was answered by testing hypothesis (H1) presented in Chapter 5 (preliminary data analysis). Also, the results and discussion was already provided. The next sections of other hypotheses are to provide for the main findings to answer all other research questions.

6.7.2 Hypotheses (H2a-H2c), (H3a-H3d), and (H4a-H4b)

In this section, the two research questions below can be answered by testing hypotheses (H2a to H4d)

6.7.2.1 Research Questions II Proposed

Research Question II: *"What are the innovation factors that can influence Australian organizations to adopt the business intelligence technologies to be appropriate to their ERP perspective?"*

6.7.2.2 Research Questions III Proposed

Research Question III: "*What kind of factors of organizational innovation can be use to indicate the difference between early adoption and non-early adoption?"*

Hence, the results of hypotheses testing are presented as follows:

Hypotheses (H2a, H2b, and H2c)

Hypothesis (H2a): Perceived benefit will be reflective indicators of technological constructs to BIDSA adoption (BEN ---> ADOPT).

As mentioned in Table 6-25, perceived benefit did not have a positive relation with technology factors to BIDSA adoption. This result indicates does not to support hypothesis H2a, which means that benefit is not a technological innovation factor that positively influences BIDSA adoption. Thus, hypothesis H2a has been rejected.

Hypotheses (H2b): Task complexity will be a reflective indicator of technological constructs to adopt BIDSA (CPLEX ---> ADOPT).

The results indicated that complexity of the system had a direct relation to adoption (ADOPT4) but it shows a negative relationship. It could be stated that task complexity was a factor that influenced the adoption of BIDSA with the level of adoption ADOPT4, and as hypothesized, it was not a positive influential technological innovation factor for BIDSA adoption. Thus, it can be summarized that hypothesis (H2b) was accepted.

Hypothesis (H2c): System compatibility will be a reflective indicator of technological constructs to BIDSA adoption (CPAT ---> ADOPT)

Based on the result shown in Table 6-25, system compatibility had a direct positive effect on BIDSA adoption with the level of adoption (ADOPT5). This means that system compatibility was a positive influential factor to adopt BIDSA at the level of ADOPT5. Hence, hypothesis (H2c) was accepted.

In addition, at the level of BIDSA adoption (early adoption and non early adoption) theorized in Chapter 2, it could be suggested that system compatibility was a positive influential factor to the early adoption of BIDSA.

Hypotheses (H3a, H3b, H3c, and H3d)

Hypothesis (H3a): Top management support will be a reflective indicator of organizational constructs to BIDSA adoption (TOPMS ---> ADOPT).

The results presented in Table 6-25 indicate that top management support had a positive relationship to adopt in BIDSA. This means that top management support was a positive influential factor for the adoption of BIDSA. Therefore, hypothesis (H3a) was accepted.

Hypothesis (H3b): Organisational size will be a reflective indicator of organisational constructs for BIDSA adoption (OSIZE ---> ADOPT).

According to table 6-25, organizational size (resources) was a significant indicator showing a positive relationship to BIDSA adoption. As such, the hypothesis (H3b) was accepted.

Hypothesis (H3c): Absorptive capacity will be a reflective indicator of organisational constructs to adopt BIDSA (ABSORP ---> ADOPT).

As expected, absorptive capacity had a positive link to adoption of BIDSA, but this was not significant at levels 0.001 and 0.05 as shown in Table 6-25. Thus, hypothesis H3c was rejected.

Hypothesis (H3d): Internal Need will be a reflective indicator of organisational constructs to adopt BIDSA (NEED ----> ADOPT).

The results shown in Table 6-25 indicated that internal Need was not a significant factor. Hence, hypothesis (H3d) was rejected.

Hypotheses (H4a and H4b)

Hypothesis (H4a): Competitive pressure will be a reflective indicator of environmental constructs to adopt BIDSA (CPET ---> ADOPT).

Based on the result in Table 6-25, it was indicated that competitive pressure had a direct positive link to adoption 3, and the competitive pressure factor was a significant indicator. It could be summarized that the competitive pressure factor influenced the adoption of BIDSA at the level of adoption (ADOPT 3). Thus, hypothesis (H4a) was accepted.

In addition, competitive pressure was also found to be a factor that affects the adoption of BIDSA for early adopters.

Hypothesis (H4b): Vendor selection will be a reflective indicator of environmental constructs to BIDSA adoption (VEND ---> ADOPT).

The results shown in Table 6-25 indicated that vendor selection was not a significant factor. Hence, hypothesis (H4b) was rejected.

Consequently, from hypotheses H2a to H4b, top management support and organizational size were found to be positive influential factors for suitable BIDSA adoption. However, the results showed that task complexity and system compatibility, and competitive pressure had a direct positive effect on to adoption of ADOPT4, ADOPT5 and ADOPT3 respectively. These were also significant factors. Thus, all the task complexity, system compatibility and competitive pressure could be considered to be factors that affect the adoption of BIDSA at the early adoption stage as theorized in Chapter 2. Therefore, hypotheses (H2b, H2c, H3a, H3b, and H4a) were accepted.

6.7.3 Hypotheses (H2, H3, and H4)

There are two research questions that can be answered by testing hypotheses (H2, H3, and H4).

6.7.3.1 Research Question IV Proposed

Research Question IV: *"Which factors are the most important in the promoting/ inhibiting of BIDSA adoption?"*

Hypotheses (H2): Technological innovation factors will positively affect BIDSA adoption.

Based on the results in Table 6-30, technological innovation was a negative influential factor to adopt BIDSA. Thus, hypothesis (H2) was rejected.

Hypotheses (H3): Organizational factors will positively affect BIDSA adoption.
The results in table 6-30 indicated that organizational factor were positively influential factor to adopt BIDSA at 0.05 significant level. Hence, hypothesis (H3) was accepted.

Hypotheses (H4): Environmental factors will positively affect BIDSA adoption.
The results showed that environment was not a positively influential factor to adopt BIDSA, and it was also not significant at levels 0.001 and 0.05. Therefore, hypothesis (H4) was rejected.

Based on the results presented in Table 6-30, it was found that organizational factors were positive influential factors for Australian organizations to adopt BIDSA at a significant level of 0.05. Other factors hypothesized were not found to be significant factors influencing BIDSA adoption. As a result, only hypothesis (H3) was accepted. Therefore, it could be concluded that the most important factor in promoting of BIDSA in an ERP perspective were organizational factors. However, as hypotheses (H2 and H4) were rejected, it could be suggested that both technological innovation and environmental factors were factors in inhibiting (less important) of BIDSA adoption in an ERP perspective.

6.7.3.2 Research Question V Proposed

Research Question V: *"Does this proposed model adequately describe previously successful adoption of BIDSA? And can it be use to predict future adoption of BIDSA?"*

Hypotheses (H5): Any innovation factors will positively affect BIDSA adoption.

As theorized based on innovation theory in Chapter 2 and 3, technological, organizational, and environmental factors can be useful to predict the successful adoption of BIDSA in an ERP perspective. As hypothesis (H3) has been accepted, the research found that the adoption of BIDSA is genuinely related to organizational factors (see Table 6-30). However, the other hypotheses were rejected (H2 and H4). This means that organizational factors can be considered as the most important predictor for the successful adoption of BIDSA. In addition, the results in Table 6-25 indicated that top management support and organizational size, which were reflective indicators of organizational constructs, were found to be significant factors affecting the adoption of BIDSA as hypotheses (H3a and H3b) were accepted. Therefore, the hypothesis (H5) was accepted.

Although Table 6-30 shows that technological innovation and environmental factors had links to adoption, they were negative influential factors and not deemed as a significant (H2 and H4 rejected). However, based on Table 6-25, as hypotheses (H2b, H2c and H4a) have been accepted, the results show that certain factors of task complexity, system compatibility and competitive pressure have played a determining role in the adoption of BIDSA (direct effects) at the stage of early adoption (ADOPT4, ADOPT5, and ADOPT3 respectively). All the factors were significant at level 0.05. Therefore, it can be stated that determining task complexity and system compatibility, and acknowledging competitors have greater likelihoods of developing higher levels of BIDSA to adopt BIDSA in an ERP perspective. Table 6-34 below indicates the results of hypotheses testing for providing a wide picture and helping to answer all research questions mentioned previously.

Hypotheses	**Effect**	**Hypotheses Testing**
BENC ---> ADOPTION	Not Sig	H2a: Rejected
CPLEX ---> ADOPTION	**Direct effect **** **CPLEX ---> ADOPT 4** (early adoption stage)	**H2b: Accepted**
CPAT ---> ADOPTION	**Direct Effect **** **CPAT ---> ADOPT 5** (early adoption stage)	**H2c: Accepted**
TOPMS ---> ADOPTION	**Sig *****	**H3a: Accepted**
OSIZE ---> ADOPTION	**Sig ****	**H3b: Accepted**
ABSORP ---> ADOPTION	Not Sig	H3c: Rejected
NEED ---> ADOPTION	Not Sig	H3c: Rejected
Hypotheses	**Effect**	**Hypotheses Testing**
CPET ---> ADOPTION	**Direct Effect **** **CPET --- > ADOPT 3** (early adoption stage)	**H4a: Accepted**
VEND ---> ADOPTION	Not Sig	H4a: Rejected
TECH ---> ADOPTION	Not Sig	H2: Rejected
ORG ---> ADOPTIION	**Sig ****	**H3: Accepted**
ENV ---> ADOPTIION	Not Sig	H4: Rejected
INNOVATION FACTORS ---> ADOPTION	**1) Direct Effect** (H2c, H2b, and H4a)** **2) ORG (Sig**)**	**H5: Accepted**

*** = value is statistically significant at the 0.001 level

** = value is statistically significant at the 0.05 level

Table 6-34: Hypotheses testing in the research

6.8 RESULTS OF TESTING THE HYPOTHESES FROM THE STRUCTURAL MODEL OF BIAM (BIAM I AND BIAM II)

Due to the results of two structural models (BIAM I and BIAM II), the overall fit indicated that the final models (see Figure 6-19 and Figure 6-20) are the best fit to the data with hypotheses H3a, H3b, H2c, H2b, H4a, and H3 (see Table 6-34) accepted while the others were rejected. These hypotheses are discussed in the next section. It can be concluded that the variance in the adoption of BIDSA as a result of innovation adoption factors, such as top management support, organizational size, system compatibility, task complexity, and competitive pressure, is highly significant because the respective C.R. values of 3.865, 3.207, 3.072, -2.169, and 2.660 are showed greater than the critical value of 1.96. In addition, the results strongly support the hypothesis (H3) (C.R. = 2.865 which greater than 1.96) within the limits of the model. According to the theoretical basis, three main hypotheses (H2, H3, and H4) were discussed as follow.

6.8.1 Technological Innovation Factors (Benefit, Task Complexity, and System Compatibility) and BIDSA Adoption

As previously shown (see Table 6-25), the three hypotheses (H2a, H2b, and H2c) explain the relationships between the exogenous variables (technological innovation factors) and endogenous variables (BIDSA adoption). Three hypothesized relationships (H2a, H2b, and H2c) were not found to be significant (benefit: C.R. = .501, task complexity: C.R. = .584, and system compatibility: C.R. = -1.138). In addition, as hypothesized technological innovation factors (H2) was also rejected because it was not found to be significant in the hypothesized direction (C.R. = -1.698) (see Table 6-30).

It was found that the three technological factors (BENCx, CPATCx and CPLEXCx) were initially expected to have direct links to adoption. As seen in Table 6-25, there is no technological factor that can significantly influence the adoption of BIDSA. However, task complexity and system compatibility have direct effects on adoption (ADOPT5 and ADOPT4) at levels 0.05 respectively. As theorized earlier about early adoption and non-early adoption, it was suggested that task complexity and system compatibility are important to be considered to adopt BIDSA for the early adopters. Therefore, this result provides partial support for technological innovation factors influencing the adoption of BIDSA (H2).

6.8.2 Organizational Factors (Top Management Support, Organizational Size, Absorptive Capacity, and Internal Needs) and BIDSA Adoption

Hypotheses (H3a, H3b, H3c, and H3d) represent the relationship between the exogenous variables (organizational factors) and endogenous variables (BIDSA adoption). Results in Table 6-25 indicate that two hypotheses (H3a and H3b) are significant since respective C.R. values of 3.865 and 3.207 which are greater than the critical value of 1.96. This result provides partial support for organizational factors influencing the adoption of BIDSA (H3). In addition, the results strongly support hypothesis H3 for which the C.R. value was indicated at 2.970 showing greater than 1.96 (see Table 6-30). Therefore, it could be concluded that the organizational factors have the most influence on the adoption of BIDSA. Hypothesis (H3) was supported.

6.8.3 Environmental Factors (Competitive Intensity and Vendor Selection) and BIDSA Adoption

As shown earlier (see Table 6-25), hypotheses (H4a and H4b) represent the relationship between the exogenous variables (environmental factors) and endogenous variables (BIDSA adoption). Neither of these two hypothesized relationships (H4a and H4b) was found to be significant (both values of C.R. lower than 1.96). As such, the hypothesis representing this relationship (H4) was not supported as the parameter estimate was non-significant (C.R. = -.806 and -.474 respectively).

It was found that the technological factors (CPETCx and VENDCx) were initially expected to have direct links to adoption. As seen in Table 6-25, there is no environmental factor that can significantly influence the adoption of BIDSA. However, competitive pressure has direct effects to adoption (ADOPT3) at a significant level of 0.05. It is also suggested that only competitive pressure is important to be considered to be adopt BIDSA for early adopters. Therefore, this result provides partial support for environmental factors influencing the adoption of BIDSA (H4).

6.9 SUMMARY

The overall objective of this chapter was to determine support for the hypothesized models by using statistical modelling. The main part of statistics technique using SEM was discussed. Using two stages the (measurement models and structural models) were found to indicate some relationship with the innovation factors and the adoption of BIDSA. The initial results from measurement models were re-specified and tested to provide a more parsimonious model which shall be used in the following stage of the structural model. This first stage improved discriminant validity and the modified measurement model provided adequate fit to the data with all indicators showing highly. After results obtained showed that all ten constructs were highly reliable, the hypothesized structural model was tested in the second stage. The finding suggested that organizational factors including top management support and organizational size indicate significant factors that influence the adoption of BIDSA. In addition, it was found that organizational factors were the most important factors affecting to BIDSA adoption at a significant level of 0.05.

However, other groups of factors (technological innovation factors including compatibility and complexity and environmental factors as competitive pressure) indicated significantly as partial supports for the adoption of BIDSA. In total, six hypothesized relationships are investigated and accepted (see Table 6-35 below). The next chapter discusses the above results in detail for answering the three research questions outlined in chapter one. This will show the significance of the theoretical and practical implications of these findings. Further, the limitations of this thesis, the directions for this thesis, and the final conclusions will be discussed.

Hypothesized Path	C.R.	RESULTS ACCPETED
H3a: TOPMSCX --- > ADOPT	3.865	**YES*** **
H3b: OSIZECX --- > ADOPT	3.207	**YES** **
H2c: CPATCX --- > ADOPT 5	3.072	**YES** **
H2b: CPLEXCX --- > ADOPT 4	-2.169	**YES** **
H4a: CPETCX --- > ADOPT 3	2.660	**YES** **
H3: ORG --- > ADOPT	2.865	**YES** **

*** = value is statistically significant at the 0.001 level

** = value is statistically significant at the 0.05 level

Table 6-35: Hypotheses accepted using standardized estimates

CHAPTER 7

DISCUSSIONS AND CONCLUSION

7.1 INTRODUCTION

This chapter brings to a conclusion this study on the adoption of business intelligence and decision support application (BIDSA) for the perspective of ERP in Australia. This chapter aims to interpret the results reported in the previous chapters (Chapter 5 and Chapter 6) and fulfil the aims of the research through answering the four research questions proposed in the first chapter. Based on Chapter 6 (See Figure 19 and Figure 20), two models of BIDSA (BIAM I and BIAM II) are developed to illustrate the innovation adoption factors that influence BIDSA for ERP user organizations to accept and adapt practices suited to their new environment in Australia. In this chapter, technological innovation, organizational, and environmental factors are discussed. These are organized into five sections.

In order to provide background and basic features on the data used in this study, in this chapter the first section summarizes the objectives of research aims. Next, the second section shows the results of descriptive statistics provided and presented in Chapter 5. Then moving into the main findings presented in this chapter, the third section presents the results of hypotheses testing. In addition, the results of all fourteen hypotheses are also discussed and summarized. In the fourth section, implications and recommendations are offered. Last, limitations and future research directions are discussed and identified.

7.2 RESEARCH AIMS

Given the growing importance of the use of the business intelligence techniques as a decision support tool in organizations, it is surprising that the factors that influence the adoption of BIDSA have not been fully investigated. Under these circumstances, the general aim of this study was to explore and investigate factors affecting the adoption of BIDSA from ERP perspective using these advanced technology and decision support tools. This study also focused on three specific aims and the following four questions were formulated as a guide for the research design in order to achieve its aim.

1) First, how do the company characteristics differ in the extent of adoption and implementation of BIDSA by Australian organizations?

2) Next, what are the innovation factors that can influence ERP users to adopt business intelligence technologies? If there is a difference, what kind of factors could be suggested differently between early adoption and non early adoption?

3) Then, which factors are the most important in the promoting/inhibiting of BIDSA?

4) Finally, does this proposed model adequately describe previously successful adoption of BIDSA? And can it be used to predict future adoption of BIDSA?

As BIDSA is a relatively recent technological innovation, this research utilized the innovation theory (Rogers 1995) in developing the research model for the adoption of BIDSA from an ERP perspective and incorporated those factors affecting the use of IT in organizations. This theoretical philosophy was derived from the organizational innovation and BI, as well as ERP literature. Based on these research questions, fourteen hypotheses were formulated from the four research questions to achieve the aims of this study. To test the hypotheses, structural equation modelling (SEM) was used to examine the relationships between innovation factors and the adoption of BIDSA for the selected group of ERP user organizations.

7.3 DESCRIPTIVE STATISTIC RESULTS

In Chapter 5, according to the questionnaire survey of 150 respondents descriptive statistics were conducted and these reported basic features of the data used in this thesis. Based on the details in the demographic aspects of BIDSA adoption, the results from the finding of the survey questionnaire are discussed below.

First, demographic responses were requested from respondents about their employee background, and the findings showed that most ERP managers were IT project managers (52%) and their working experience in their current position was in a range of 1 to 5 years (82%). Not surprisingly, based on IT knowledge, respondents (92%) indicated ERP managers are equipped with BIDSA knowledge necessary for adoption and implementation. These results also indicated that the sample group of ERP user organizations in this study is good representation of the whole population.

Second, ERP managers were also asked to provide their company background information. Their results showed that over 70% were large companies that had been using BIDSA from 3 to 10 years (72.7%). According to the descriptive statistics results, it can be concluded that the sample group of ERP user organizations in this study represent the whole group.

ERP managers were also asked the extent to which BIDSA has been implemented in Australia. These findings showed that organizational size and time of use BIDSA of the firms were significant in Australia. These results supported the main research hypothesis (H1) that the adoption of BIDSA is significantly related to enterprise resources and time consumed for innovation diffusion to adopt the technology (Rogers 1995).

7.4 SUMMARY OF THE RESULTS OF HYPOTHESIS TESTING AND RESEARCH QUESTIONS

Based on the theory of Diffusion of Innovations (DOI) by Rogers (1995), there are three contexts of organizational innovation factors that affect adoption and implementation of technology in firms: 1) technological innovation context; 2) organizational context; and 3) external environmental context. Results of this research suggest that the adoption of BIDSA in an ERP perspective can be assigned via the use of innovation factors. In agreement with Rogers (1995) this study found that the adoption perspective is useful to evaluate the characteristics of an organization that make it receptive to innovation and change. In addition, studies using the diffusion perspective attempt to understand why and how an innovation spreads and what characteristics of the innovation lead to wide spread acceptance. After an organization has adopted an innovation, use of the innovation has to spread within it for the innovation to provide its full benefits.

Consistent with this statement, results of this research confirm links between the innovation factors: 1) technological innovation; 2) organizational; and 3) environmental in the models of BIAM. These results are also in agreement with the few studies that relied on the theory of innovation for developing hypotheses about relationships among the innovation factors (e.g.

Bradford & Florin 2003; Chau & Tam 1997; Kamal 2006; Thong 1999; Tornatzky & Fleischer 1990; Zailani, Ong & Shahnon 2006)

As summarized in the Table 6-34, it was found that the factor 'organization' is the most important factor to influence in adopting BIDSA (H3 accepted). Moreover, top management support and organizational size (resources) were shown to be very important reflective indicators of organizational constructs as significant factors of BIDSA adoption (H2a and H2b accepted) (Hwang et al. 2004; Ramamurthy, Sen & Sinha 2008). The others (absorptive capacity and internal need) (H2c and H2d) are rejected. However, 'technology' and 'environment' factors were not to make a significant contribution to BIDSA adoption (H1 and H2 rejected). It was found that all three technological innovation factors (perceived benefit, task complexity, and system compatibility) were not a significant contribution to BIDSA adoption (H1a, H1b, and H1c rejected), while all the two factors (competitive pressure and vendor selection) of environmental factors are not accepted as important factors (H3a and H3b rejected).

However in particular related to direct influence to the early stage of BIDSA adoption the three factors of task complexity, system compatibility, and competitive pressure were significant contributors as a direct effect influencing specifically stages of BIDSA with extended business applications (ADOPT4), BIDSA with BIDSA with real-time applications (ADOPT5), and BIDSA with data analytic (ADOPT3) respectively. The three factors indicated as important for early adopters of BIDSA adoption were theorized in Chapter 2. In particular, task complexity and system compatibility (a reflective indicator of technological constructs) and competitive pressure (a reflective indicator of environmental constructs) are consistent to the works (e.g. Chang et al. 2008; Hwang et al. 2004; Ramamurthy, Sen & Sinha

2008; Thompson, Lim & Fedric 2007) and are suggested to be likelihood determinants affecting the BIDSA adoption.

In summary, based on the proposed model as theorized in Chapter 3 (see Figure 3-1) six hypotheses (**H3, H3a, H3b, H2b, H2c, and H4a**) were accepted (see Table 6-35). From this finding, it can be suggested that factors from organizational context are the most important to consider for development and adoption of BIDSA in ERP user organizations (Bowonder, Miyake & Linstone 1994; Thong 1999). Thus, H3 is accepted (see Table 6-35). In particular, the specific factors of top management support and organizational size (resources) play significant roles for adopting and developing BIDSA by ERP user organizations (Grover 1998; Hwang et al. 2004; Thong 1999; Watson & Haley1997). Thus, H3a and H3b are accepted respectively (see Table 6-35). These hypotheses (H3, H3a, and H3b) can be applied to answer Research Questions II, III, IV, and V (see section 6.7.2 and section 6.7.3).

Moreover, the findings also indicated that task complexity and system compatibility are considered to be significant determinants of technological innovation factors for ERP user organizations to adopt and develop BIDSA (Jeon, Han & Lee 2006; Ramamurthy, Sen & Sinha 2008; Thong 1999). Thus, H2b and H2c are accepted (see Table 6-35). In addition, another finding of this research showed that business competition is related to BIDSA adoption for ERP user organizations (Grandon & Peason 2004; Hwang et al. 2004; Jeon, Han & Lee 2006; Premkumar & Margaret 1999). Thus, H3a is accepted (see Table 6-35). These hypotheses (H2b, H2c, and H3a) can be used to answer Research Questions II and III (see section 6.7.2).

As all Research Questions can be answered theoretically as well as statistically, consequently these are among the critical factors and are anticipated to be factors as critical and beneficial for the initial adoption and introductory implementation phase of BIDSA adoption. Therefore, it could be concluded that the BIAM models (BIAM I and BIAM II) adequately indicate previously successful adoption of BIDSA and it is used to predict future adoption of BIDSA as the specific model showed the above hypotheses as accepted.

7.5 IMPLICATIONS FOR THEORY AND PRACTICES

An important implication of this research is that this study is one of among only a few which have empirically tested the model of adoption of BIDSA in the context or ERP user organizations in Australia. Therefore, this study contributes new knowledge to the research literature and for other researchers. Moreover, the findings of this study can be utilized as a guideline for future study that is intended to investigate the phenomenon in other Asia Pacific settings. In addition, in particular the findings of this study have also validated the theory that technological innovation adoption, as it is widely applied in various industries in American or European countries, is applicable in the context of an ERP perspective. Therefore, it is expected that researchers in the fields of IT/IS/ICTs (e.g. business intelligence and decision support applications) will use the proposed model and the important variables of this study and test them in potentially various situations.

The research focused on BIDSA technological innovation in an ERP perspective, and considered this from organizational innovation adoption context. The implications from this are beneficial to business organizations in Australia. This study focused on: 1) technological innovation including benefit, complexity, and compatibility); 2) organizational factors including top management support, organizational size, absorptive capacity, and internal need); and 3) environmental factors including competitive pressure and vendor selection) discussed in Chapter 2 and Chapter 3.

The results indicated that only top management support, organizational size, task complexity, system compatibility, and competitive pressure were significant organizational innovation factors in the context of BIDSA adoption with an ERP perspective in Australia. In contrast, the results in this study indicated that benefit, absorptive capacity, internal need, and vendor selection are not important in BIDSA adoption in Australia. In addition, it was found that organizational factors were significant and were the most important constructs in BIDSA adoption. The significant theoretical and practical implications of the findings are presented and discussed below.

7.5.1 Perceived Benefit as a Technological Innovation Factor

Perceived benefit is the expected advantage these technologies will bring to a company when there is a need for adoption. This benefit would inspire an organization to meet economic profitability, time and effort savings, and cost reduction (Clemons 1991). As previously discussed, benefits as perceived by users have been found to be an important factor to affect the adoption decision (Jeon, Han & Lee 2006; Lee & Shim 2007; Premkumar & Roberts 1999; Ramamurthy, Sen & Sinha 2008; Thong 1999). The significance of perceived benefits means that organizations expect and need information to show that substantive benefits from the innovation are feasible before its adoption can be considered. That is especially true in the context of major investments required for BIDSA.

However, in this study perceived benefit was not found to be significant in the process of adopting BIDSA (see Table 6-25). Past information systems research indicates that organizations that adopt information technology at different times may have distinct perceptions regarding the adoption of a particular technology (Dillon & Morris 1996; Dos Santos & Peffers 1995; Iacovou, Benbasat & Dexter 1995). Although a perceived benefit is a key factor considered in making the adoption, it may not have much of an influence on the extent to which the innovations gets infused within the organization, specifically in instances where innovation is not voluntary. A major investment in an innovation such as BIDSA is rarely voluntary. However, from a firm's perspective, relative advantage or perceived benefit plays a significant role in the adoption and determination of the manner in how and the degree to which the innovation is employed. Once these decisions are made, the perceived benefit may have less of an influence. In this study, the potential benefits from BIDSA are still considered low because in an ERP perspective most organizations have adopted only one BIDSA innovation (data warehouse) (Hawking, Foster & Stein 2008). In addition, it is no longer the perceptions of the benefits potential that the enterprise is concerned with but the actual benefits that may have been realized or are expected to be realized. The results confirmed to other research studies on perceived benefits as a non potential determinant (Hwang et al. 2004; Ramamurthy, Sen & Sinha 2008).

Therefore, it might be that BIDSA benefits are shown to be intangible and inconclusive, and projects take longer than expected, BIDSA projects require significant up-front investments in both effort and money, with benefits realizable over the long term. It could be implied that ERP user organizations may not consider adopting BIDSA unless having a newly innovative need. Having made a decision to adopt an innovation, actions to successfully execute and manage the innovation project become more important than benefit. From this research with regarding to technological innovation, it is suggested that task complexity and system compatibility are better consideration to be positive determinants affecting BIDSA adoption. This will be discussed in the following sections.

7.5.2 Complexity as a Technological Innovation Factor

Rogers (1995) explained that product complexity would play an important role in the adoption of technology. Markus (1983) and Keen (1983) showed that fail implementations were often that IT literature due to positive/negative resistance to the adoption of IT innovations. This is because BI innovation containing many techniques is complex, and has a potential for major organizational changes. This related to the degree of professional knowledge the members of the organization is perceived to understand and use. The results of this study have confirmed that the adoption of BIDSA can be achieved by concentrating on task complexity of the BIDSA system of the stage of BIDSA with extended business applications to users in organizations (see Table 6-25). BIDSA with extended business applications has the ability to access enterprise data in the warehouse for addressing business questions that span multiple functional areas including CRM. BIDSA using CRM is a decision support application facilitated by data warehouse with the objective of maximizing the lifecycle value of customers, which entails focusing on many aspects of business, from marketing, sales, operations, and service, to establishing and sustaining mutually beneficial relationships with customers (Kimball & Ross 2002).

The results show that the significance of complexity reinforces that fact that the task complexity of BIDSA technology can adversely influence its adoption. The negative relationship between complexity and BIDSA adoption seems quite natural and is confirmed by Tornatzky & Kline (1982). This finding is consistent with other research studies on complexity relating to the adoption of technology (Jeon, Han & Lee 2006; Ramamurthy, Sen

& Sinha 2008; Thong 1999). As mentioned above, the high complexity of BIDSA sets up significant challenges in understanding not only the basic technology, but how it fits from the existing architecture and aligns with other technology BI components (e.g. CRM, SCM). Such complex new innovations may demand development of significantly new skill sets and additional competency within the firm. The research suggests that BIDSA complexity is particularly problematic in an organization context without adequate training and appropriate integration (Joshi & Curtis 1999; Kimball, Reeves & Thomthwaite 1998).

7.5.3 Compatibility as a Technological Innovation Factor

System compatibility is the degree to which it is perceived as being consistent with existing vision, past experiences, and needs of ERP users (Thong 1999). When a customized or new solution of BIDSA is required, these external designs of hardware and programming are accompanied by system errors, delays, and need for maintenance. In other words, compatibility among innovative technology and its users as well as the system, and operational procedure of the enterprise, can also influence the organization's adoption of innovative technology (Kwon & Zmud 1987). In addition, these may slow up the adoption process and discourage the end users (Harrison, Mykytyn & Riemenschneider 1997; Thong 1999). As organizations realize that the effective and strategic decision support of enterprise wide functions is integral to their success, decision support activities are becoming more integrated with their business functions. ERP uses IT to achieve a capability to plan and integrate enterprise-wide resources (e.g. integrating the applications and processes of the various functions). This system integration is an important means of achieving enterprise integration for decision making (Alsene 1999; Davenport 1998). This requires the BIDSA to become compatible with other systems, standards, and work procedures in the organization. In BIDSA, technical incompatibilities relating to standards, data modelling, or hardware/software applications as well as BIDSA platforms are major inhibitors to BIDSA adoption (Joshi & Curtis 1999; Kimball, Reeves & Thomthwaite 1998).

Due to the radical nature of BIDSA innovation, the results in this study indicate that compatibility being found to influence the decision to adopt BIDSA in consistent with previous research (Akbulut 2002; Chwelos, Benbasat & Dexter 2001; Jeon, Han & Lee 2006; Thong 1999). Emergence of the compatibility of BIDSA with the organization's various functions and work practices and culture as key variables confirm earlier findings in the IS literature on major innovations and emphasizes the fact that BIDSA is different from routine traditional individual software applications. It might be concluded that BIDSA components represent more of a foundation-type system that triggers major changes to data ownership and sharing, alter access and usage patterns, change how jobs are performed, provide organization-wide decision support, and drastically influence and transform organizational work practices and business processes as well as generate more efficient, accurate, responsive decisions and better exploit other BI applications (e.g. CRM, BI real-time opportunities) (Wixom & Watson 2001).

7.5.4 Top Management Support as an Organizational Factor

It has been argued that positive organizational factors contribute to the success of technology adoption (Bowonder, Miyake & Linstone 1994). It comes as no surprise that top management plays an important role in the process of adopting BIDSA (Hwang et al. 2004). The engagement of top management is a key to the adoption of BIDSA technology as top management can stimulate change by communicating and reinforcing values through an articulated vision for the ERP organization (Thong 1999). Moreover, top management support is critical in ensuring that resources required for adopting and implementing BIDSA technology will be readily available when they are needed (Delone 1988). If the top management level supports the adoption of BIDSA, assistance for the required resources will be much more easily acquired (Hwang et al. 2004). Further, because BIDSA is a radical innovation that could trigger politically charged issues, it demands the highest level of support, engagement, and commitment from top management. The project team members will worry less about the shortage of resources and can focus more on the other matters related to the adoption of BIDSA. Furthermore, it is demonstrated that the greater the top management support is, the easier it is for an organization to overcome the difficulty and complexity faced in the adoption of BIDSA (Watson & Haley 1997). In other words, it could be suggested that top management support is required to overcome the resistance to change. As indicated by a number of researchers (Grover 1998; Hwang et al. 2004; McFadden 1996), top management support is a key factor affecting the adoption of information technology.

In this research, support from top management was found to be a strong indication that adoption of BIDSA technology will go smoothly. It can be explained that the lack of committed support from top management can be a barrier to the effective use and subsequent adoption of systems, particularly for enterprise systems such as BIDSA (Guimaraes, Igbaria & Lu 1992; Kwon & Zmud 1987). As BIDSA components are often very expensive, resource intensive, and carry a high risk of failure, it is important to pursue the successful implementation by providing resource intensive innovations, continued management support and commitment in order to make available or mobilize adequate slack resources within the adopting organization (Bourgeois 1981; Damanpour 1991). The results of this study validate this belief as did other prior research. Based on Table 6-25, top management support is the most significant, discriminant index to distinguish whether or not to adopt BIDSA technology in this type of organization. Being the most important factor influencing ERP enterprises to adopt BIDSA, this finding is in line with the findings to adopt other types of information technologies (Wixom & Watson 2001).

7.5.5 Organizational Size as an Organizational Factor

With regard to organizational size, various literature demonstrated that the larger the organization scale, the more likely will the organization adopt new technology (Rogers 1995; Tornatsky & Fleischer 1990). Grover & Golslar (1993) likewise verified that a larger organization would possess more resources, a better foundation, and better capacity for undertaking the risk. In other words, larger organizations tend to adopt IT easily due to greater economies of scale. Currently, BIDSA technology and it applications are too costly, with the most common cost categories of BIDSA including hardware, software, training, integration, and testing. Generally, speaking, it will cost in excess of US$1 million to build a full-scale BIDSA (e.g. data warehouse, OLAP, data mining, other extended applications) application/system. For most companies including ERP user enterprises, it is quite a large expenditure for this application, and companies would indeed require much funding to implement this kind of innovation technology investment. If adoption abandonment occurs, this may result in a huge financial loss for the enterprise. Given this information, the research suggests that the size of the enterprise will play an important role in the decision-making processes for enterprises in Australia. In this study (see Table 6-25), the value of regression weight (0.350) of the size of the organization is ranked as the second highest. That is, in addition to the factor of top management support, the size of the company is the second most important discriminant index.

7.5.6 Absorptive Capacity as an Organizational Factor

The adoption of a technology innovation requires more than investing in the financial and technological resources to acquire or build BIDSA. The ability to create and nurture an environment to absorb and transfer the skill and knowledge bases to exploit the nuances of an innovation is a key to innovation adoption. IT knowledge could facilitate the rich information exchanges and assist the problem solving among IT and line managers that is critical in enabling an organization to move beyond IT applications toward applications that provide business value. Organization absorptive capacity is a strong predictor of an organization's ability to adoption innovations (Cohen, WM & Levinthal 1990) however a key finding in this study is not the significant influence of absorptive capacity as this variable has been cited as important (Cohen, WM & Levinthal 1990; Fichman 1992; Ramamurthy, Sen & Sinha 2008). However, the results of this finding are consistent to the work by Boynton, Zmud & Jacobs (1994).

As skilled workers and human capital tend to enhance the absorptive capacity of firms, this research suggests that the presence of skilled staff will not encourage technological adoption. In addition, intuitively training workers should also enhance a firm's absorptive capacity. Given the importance of absorptive capacity, the implication for smaller firms may be that growing large is not the only pathway, but that they could explore other roads to increase absorptive capacity (e.g. partnering with other small firms as consortiums, trade partnership) (Ramamurthy, Sen & Sinha 2008). In this study, almost all (80%) are large organizations with highly innovative systems (ERP) that could have the skills needed to deal with the tacit component of transferred knowledge and needed to modify this imported knowledge. When organization members possess a greater prior knowledge's base about the object, they can absorb new knowledge more effectively (Lane, Salk & Lyles 2001; O'Dell & Crayson 1998).

Hence, ERP staffs have good technical knowledge relating to the BIDSA application and should be strong units in easily applying such new knowledge as BIDSA.

According to Hughes & Scott Morton (2006), the adoption of new IT requires complementary organizational innovations asking for particular skills that are not usually available, and it also determines that need for additional personnel training (Bresnahan, Brynjolfsson & Hitt 2002). Positively, ERP user organizations better provide professional training relating to the innovative IT (BIDSA) for new and current users. This linkage may show positive association between having a more professional staff and innovation (Damanpour 1991; Fichman 2001). They have possibly been trained very well in advance of IT applications especially critical in the context of an IT infrastructure type innovation such as data warehouse or ERP. Moreover, they were probably already endeavouring to perform the adoption knowledge of BIDSA. Thus, the absorptive capacity was not an important factor that influenced BIDSA adoption from an ERP perspective.

7.5.7 Internal Need as an Organizational Factor

The adoption of information technology actually results from internal needs (Grover & Golslar 1993; Watson & Haley 1997) and so it would be helpful to adopt BIDSA technology after the organizational decision-makers completely understand the internal needs to necessitate such an adoption. Prior research by Zmud (1984) and Chen et al. (2007) showed that the internal need of an organization is an important factor, which affects the adoption of a new information technology.

This study however, found that the internal needs for business organizations to adopt BIDSA technology are not significant factor for BIDSA adoption in an ERP perspective. Hwang et al. (2004) suggested that BIDSA adoption heavily depends on the internal needs if the organizations believed in the perceived benefits of the innovation such as speeding the reaction, improving the quality of the service, cutting operating costs, providing reliable information in a timely manner, and increasing relative competitive advantage. In this study, perceived benefits were found not to be a significant factor affecting the adoption of the BIDSA innovation. It seems that investing in BIDSA does not generate direct profits for business organizations but it will assist in providing better decision support for managers with intelligent solutions. As a result, this study believes that internal needs do not have a great influence on the decision to adopt BIDSA.

7.5.8 Competitive Pressure as an Environmental Factor

Many scholars found that competitiveness of the environment is insignificant in affecting the decision to adopt IT (Jeon, Han & Lee 2006; Thong 1999; Thong & Yap 1995). However, with regard to the uncertainty of the environment, especially competitive intensity, Kwon & Zmud (1987) argued that in more turbulent and unstable environments, a more rapid adoption of innovative technology should be carried out for better competition. Globalization and rapid change in information preferences (e.g. customers) brought fiercer market competition, along with the accompanying change in the industry environment. The organization requires IT assistance to reduce this uncertainty. In addition, Lee (2004) indicated that many firms adopted innovations because their competitors were doing so. This means that it was the combination of strategic necessity and competitive intensity within the industry that drove the adoption decision among organizations.

As enterprises always strive hard to raise their competitive advantages by adopting new technology, it come as no surprise that these enterprises work through evaluation and assessment about timing, cost, and underlying opportunity to adopt BIDSA to gain strategic advantages and raise the market entrance costs for their competitors (Hannan & McDowell 1984; Levin, Levin & Meisel 1987). According to Link & Bozeman (1991), competition increases the likelihood of innovation adoption. This means that dealing with competitors is an important factor affecting BIDSA adoption. Many findings by Grandon & Peason (2004), Hwang et al. (2004), Mehrtens, Cragg & Mills (2001), and Premkumar & Margaret (1999) support that pressure from competition is an important factor for organizations in adopting technology to maintain sustainable competitive edge over their rivals.

The results of this study have confirmed the hypothesis that the adoption of BIDSA can be achieved if the BIDSA technology in the stage of analytic application can be used to deal with competitors in ERP user organizations. This application of BIDSA (e.g. OLAP, data mining) enables analytics, executives and managers to develop useful insights through a multidimensional presentation of the warehouse data. This technology would be a great help in finding answers to such business questions as to find the daily sales for a given category, drill down to the product level, and roll up to the month level for determining monthly sales of promoted items, or drill through to the transaction level to find shopping patterns. Finally, BIDSA can bring the vision of a totally different way of conducting business to reality in dealing with competitors (Kimball, Reeves & Thomthwaite 1998). It can be suggested that many top managers and boards of directors view BIDSA as more strategic than administrative. Thus, it can be concluded that the competitiveness of the environment may necessarily provide the direct push in influencing ERP users' intention to adopt BIDSA technology.

7.5.9 Vendor Selections as an Environmental Factor

Information technology (IT) outsourcing is one of the major issues facing organizations in today's rapidly changing business environment (Olson & Wu 2008). Vendors can be helpful in providing complete products, better technological capability and knowledge, and familiarity to particular information technologies to assist in their adoption (Kimball 1996). However, the vendor selection process requires a great deal of attention and should not be taken in a rush (Michell & Fitzgenerald 1997). Although the particular vendors have the capability to provide the knowledge and assistance for the adoption of BIDSA technology, the implementation and adoption of this technology still needs the expertise of internal in-house functional employees, and the technology must be integrated into and hence be compatible with the existing information systems. As BIDSA technology is not only a software package, and the implementation plan proposed or developed by vendors may not be completely customized for ERP users.

According to Chau (1995), SMEs tended to focus on selecting software packages provided by vendors rather than developing information systems in-house, and SMEs relied more on packaged software than large enterprises do (Heikkila, Saarinen & Saaksjarvi 1991). In this study, almost all ERP organizations with more than 800 employees which are identified as large organizations (74.3%) (see Table 5-5) might consider on how to shape the organization's business with specifically customized systems. Thus, the results in this research confirmed that selection of vendor plays an insignificant role in the adoption of BIDSA. This is consistent with the work relating to BIDSA by Hwang et al. (2004) that selection of vendor has no obvious influences on the adoption of data warehouse technology.

7.6 TOWARDS AN EFFECTIVE DECISION SUPPORT INNOVATION ADOPTION FOR ENTERPRISE SYSTEMS

Currently, organizations continue to increase spending on information technology (IT) and their budgets continue to rise, even in the face of potential economic downturns (Kanaracus 2008). Many factors have been considered to be determinants for adopting and implementing innovations in organizations. This study has confirmed that by providing task complexity, system compatibility, top management support, organizational size, and competitive pressure, senior managers can be motivated to adopt and implement business intelligence applications in an ERP perspective. When organizations understand innovativeness, particularly task complexity and system compatibility, these kinds of factors will be considered in terms of easy to use and the characteristics of IT in assisting decision-making. In addition, because of higher competitiveness in the global market, this factor is considered for business organizations managing multi dimensional information to accept BIDSA for providing better products and services. However, mainly by taking these factors into consideration during the implementation, top management and organizational scale factors show necessary supports for making BIDSA implementation smoothly.

This research is important in that it examines the factors that influence the adoption of BIDSA in Australia. Moreover, it is significance in adding this to the different cultural and international decision support innovation literature in which important organizational, technological, and environmental factors need to be taken into account when transplanting decision support technologies worldwide. The outcome of this study could lead to improve higher level of business decision-making which could lead better business performance by using BIDSA. In addition, it can assist in formulating efficient decision support innovation systems in worldwide and cross-cultural practices.

7.7 THESIS LIMITATIONS AND EXTENSIONS

Delon, Ruyter & Lemmink (2004) stated that part of the importance of any research is to realize its limitations. This thesis makes a contribution to the degree of innovation adoption literature, but although this study has provided relevant and interesting insights into the adoption of BIDSA in an ERP perspective, it is important to recognize its limitations. There are several limitations that need to be identified. These will be discussed in terms of the context of this research, the sample chosen, the constructs' measures, and the analytical approach used to perform structural equation modelling (SEM). Nevertheless, these limitations also present opportunities for future research.

First, according to VanDijk (2005) significant spatial disparities still persist in the intensity of ICTs adoption and use (e.g. BIDSA). Rogers (1995) and Thong (1999) have suggested that different cultural contexts may affect how enterprises accept different innovations. Therefore, caution about generalizing the results of research must be taken, as these results reflect the BIDSA innovation adoption's perspective in the context of enterprise wide system organizations. It is possible that these factors could be significant when applying the models to a different sample and this could be used it to confirm the results of this research.

Second, as mentioned by Jorgenson & Stiroh (1999) and Jorgenson (2001), information technology has changed rapidly. The presenting data relating to IT and decision support techniques were initially collected in 2007. The adoption profile is unlikely to be the same if the analysis of the BIDSA technology was conducted today (2009). This is because diffusion of BIDSA in ERP perspective is continuing. Thus, future research could replicate this study to determine the rate of diffusion of the use of BIDSA.

Third, another important limitation of this thesis is related to the criteria used in selecting the population frame (the sample of this thesis). Australian ERP users have been included as samplings for the thesis, however, only SAP enterprises in Australia were selected as a suitable group for collecting data and performing analysis due to the limited time frame. This relatively small amount of sample data may reduce the power of the statistical test as the sample used for analysis for levels of using BIDSA drawn from the selected ERP population was relatively small. However, the results of the study were satisfactory in terms of the standard statistical tests of structural equation modelling and information requirements for analysis of the research questions of the thesis. Future research, thus, can also expand on the present study using samples of ERP users with other vendors or other countries with varying environments.

Fourth, the survey questionnaire method might have limitation associated with data collection. Although care was taken to reduce the limitation of the method, possible response biases still exist. In addition, this method needs appropriate analysis by presenting acceptable statistical values to provide good results, however the limitation needing to be addressed in regard to the analytical technique (e.g. structural equation modelling) used in this thesis is the ability to assess the discriminant validity and model estimation of result quality. More importantly, specific groups may be investigated with careful consideration of the sample size, with the recommendation of at least 100-150 cases for each group (Hair et al. 2006). This might reduce the power of the statistics showing a model fit (Kline 2005).

7.8 RECOMMENDATION FOR FURTHER RESEARCH

Apart from the limitations of the study, this research also provides an opportunity for future research. Although this research has developed an effective innovation adoption model relating to decision support, many profitable areas for future research remain. Given that the results of this thesis are limited to Australian ERP perspectives, findings could be different when other cultural groups are considered. The models of BIAM I and BIAM II were developed based on small sample groups with specific ERP perspectives. This suggests a need for more cross-cultural research to identify whether other innovation adopters behave in the same way, or whether there are any issues raised about IT adoption. Thus, the proposed model of innovation adoption for BIDSA needs to be tested in different types of organizations and different groups of respondents to confirm the results of this thesis.

In addition, more specifically despite the fact that the business intelligence and decision support application models (BIAM I and BIAM II) have been already generated, it is possible to find out whether moderators including industry, size, stage of adoption, and other aspects of organizations affect the influence of all determinants toward usage and adoption. In order to find out more about the impact of moderators on the influence of determinants towards usage and behaviour intention of BIDSA, the next suggestion in SEM data analysis could be related to multiple-group analysis. This may determine whether there are any differences between or among groups and to investigate whether there are any significant differences between or among them. The most common SEM estimation procedure is maximum likelihood estimation (MLE), and this has been found to provide results with sample sizes as recommended minimum sample size of 100-150 cases to ensure stable MLE solution (Hair et al. 2006). In this regard, caution is required to generalize the findings from moderators to the population. Future research can apply these models to investigate multi-group analysis with the total population of ERP user organizations.

7.9 SUMMARY OF RESEARCH

This study focused on the use of BIDSA in ERP user organizations in Australia. Such a useful conceptual model for the successful adoption of BIDSA, these theoretical models (BIAM I and BIAM II) have been grounded by initially using Rogers' model of innovation diffusion. This research extended the Rogers' model to the research context of BIDSA adoption by applying to organizational adoption in the Rogers' model by suggesting that the BIAM models have been designed to accelerate diffusion of an information technology (BIDSA) are related positively to its rate of adoption. Thus, the Rogers' model of innovation diffusion has been useful for the analysis of BIDSA adoption.

The aim of this study was mainly to explore factors affecting the adoption of BIDSA in Australian ERP user enterprises. This chapter has discussed the results of the research findings by utilizing the descriptive statistics and structural equation modelling techniques outlined in Chapter 5 and 6. The significant theoretical and practical implications of the research finding are also discussed in this chapter.

Results from statistical analysis of the quantitative questionnaire survey data reveal insights into the key factors that influence the use of BIDSA in organizations in Australia. As theorized by BIAM models, the main findings indicate that organizational, technological, and environmental factors have an effect on the adoption of BIDSA in ERP organizations. However, this research found that the organizational factors are considered as the most importance affecting the BIDSA adoption. For an ERP perspective, the perception of top management support and organizational size regarding the use of BIDSA were the major facilitating majors, where as technological and environmental factors were inhibiting factors for the use of BIDSA.

In addition, specifically some factors were found to be direct effects to particular stage of adoption as theorized in scope of diffusion. All factors discussed below had direct effects to the stage of early adoption as classified in Chapter 2 in BIDSA adoption while nothing was found in the direction of direct effect for non-early adoption. First, system compatibility that was a technological innovation factor is considered to be a direct effect to the stage of BI real-time monitoring in BIDSA adoption. Second, task complexity was found as a directly push effect to the stage of BI with extended business applications in the early adoption stage. The last direct effect to the stage of BI analytics is competitive pressure which is the external factor.

Based on the finding, this chapter has summarized and discussed the results of findings and implications in innovative decision support for enterprise wide systems. It has also outlined the results of hypotheses testing for the thesis along with implications for theory and practice. This study found that there is room for growth in use of the BIDSA technology for many enterprises in Australia and others. The study provides suggestions for developing the use of BIDSA in this country to be successful. In addition, as the models of BIAM I and BIAM II have been validated the models for adoption of BIDSA that were delivered from the findings of this study can provide guidance for decision-makers of ERP enterprise to evaluate and improve their use of BIDSA. The author hopes that from the validated models these specifically useful findings of this study contribute knowledge to increase understanding of the benefits regarding the use of BIDSA for ERP perspectives in the country of Australia.

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APPENDIX A1

A1: QUESTIONS TO BE ASKED FOR EXPLORATORY STUDY

This short interview is a part of Ph.D. research by School of Management and Information Systems, Victoria University, Melbourne VICTORIA. The aim of this study is to examine the use of business intelligence and decision support applications by Australian business organizations. The results will be very useful in contribution of "Business Intelligence Adoption" research.

Please answer the following questions: (Company No. ________)

1. What is the name of your company?

   ____

2. What kind of core technologies/ components/ processes/ applications of business intelligence are you currently using or expecting to adopt in your company?

   ____

   ____

   ____

   ____

3. What do you think of sorts of factors that influence the adoption of business intelligence and decision support applications?

   ____

   ____

   ____

   ____

APPENDIX A2

A2: RESULTS OF EXPLORATORY STUDY USING SHORT INTERVIEWS

During the month of August 2007, short semi-structures interviews (exploratory study) were conducted at each for twenty ERP users (twenty ERP user organizations) in Australia. Each interview took approximately 10 minutes to complete. Participants were IT managers (e.g. CIO, IT executives, IT project managers). Information by interviewing different ERP users have been described into two objectives according to the degree to which they have adopted the BIDSA and the potential factors positively affect BIDSA. These summarised points are categorised in Table A2- 1 (see the next page).

Summary of Characteristics of BIDSA in Australian Businesses			
Company	**Level of using BIDSA**	**Potential Factors Influencing BIDSA Adoption and Use**	**Remarks**
Firm A1	• ETL • Data Warehouse • BPM	• Business Process • Management Vision • Barriers	
Firm A2	• Data Warehouse • Business Application	• Cost • Business Compliance	
Firm A3	• Data Warehouse • Business Application	• Corporate Support • Standard of Systems (e.g. Reporting) • Business Requirement (e.g. Complexity of Process)	
Firm A4	• Data Warehouse • ETL • Reporting System	• Cost • Political issues • Management Support • Company Infrastructure • IT Governance • Vendor selection • Legacy System Consolidation (e.g. Compatibility) • Business Drivers (e.g. Market) • Reporting Strategy	
Firm A5	• Data Warehouse • Portal • Business Application • Real-Time Application	• Benefits • Training Provided • Type of Industry • Globalisation (e.g. Image, IT governance)	
Firm A6	• Data Search System • Data Presentation • BI Server (e.g. Data Warehouse, OLAP)	• Management Support • Benefits (e.g. Reporting) • Business Content (e.g. Processes) • Structure (e.g. Organisational Readiness) • Governance (e.g. Data Warehouse Governance	
Firm A7	• Data Warehouse • Reporting Application • Extended Application	• Business Need • Regulatory Requirement (e.g. Compatibility) • Benefits	
Firm A8	• Data Warehouse • Analytics • Reporting	• Change Management (e.g. Compatibility)	
Firm A9	• Data Warehouse • BI application • Analytics	• Performance Measurement • Benefits • Compatibility	
Firm A10	• Data Warehouse • BPM	• Benefits • Organisation Readiness (IT and Staff knowledge)	
Firm A11	• Data Warehouse	• Risk • Compatibility • Ease of Use	
Firm A12	• Data Warehouse • Business Application	• Cost • Ease of Use • System Compatibility • System and Data Quality	

Firm A13	• Data Warehouse • BPM	• Cost • Business Requirement • CEO Support	
Firm A14	• Data Warehouse • DSS • EIS • ESS • KMS	• Benefits (e.g. System Quality) • Compliance • Efficiency • System Requirement (e.g. Compatibility)	
Firm A15	• Data Warehouse	• System Quality • Ease of Use • IT Governance	
Firm A16	• Data Warehouse • Business Application • SEM	• Ease of Use • System Compatibility	
Firm A17	• Data Warehouse • BI Integrated Application	• Cost • System Reporting (e.g. Quality)	
Firm A18	• Data Warehouse • Analytics • Business Application • Real-time Application	• Management Support • CEO Commitment	
Firm A19	• Data Warehouse • Business Application • Reporting Application	• Benefit • System Infrastructure • User IS knowledge	
Firm A20	• DSS • ESS • KMS	• Organisation Scale/Cost • User Participation • User IS Knowledge • Benefits • Ease of Use	

Table A2-1: BIDSA in Australian Businesses

However, according to Table A2-1, these ERP firms have been categorised into four levels based on the level of BIDSA adopted as shown in Table A2-2.

The Characteristics of 20 ERP firms sample					
Firms	**Firm** A20	**Firm** A4 A11, A14, A15	**Firm** A1, A6, A8, A10, A13,	**Firm** A2, A3, A7, A9, A12, A17, A19,	**Firm** A5, A16, A18,
Level of Adoption of BIDSA	**5%**	**20%**	**25%**	**35%**	**15%**
	Level I	**Level II**	**Level III**	**Level IV**	**Level V**
	• Basic DSS	• DW	• DW • Analytic Applications	• DW • Analytic Applications • Extended Business Applications	• DW • Analytic Applications • Extended Business Applications • BI Real-time

Table A2-2: The characteristics of ERP users sample

For factors associated with the adoption of BIDSA, most managers were concerned about risks in term of financial budget issues. Most believed that using or not using BIDSA depended on the budget allocated by their top management. Next, most managers perceived that if the firms do not implement the BIDSA, the firms were facing stiff competition and increased uncertainties. This opinion is supported by the following comments:

Firm A 16 "…the analytical solutions of BI which relies on a data warehouse can provide the necessary information and generate the way to increase value added to products or services".

Firm A 9 "…..to compete and manage effectively in today's global business environment, many ERP firms use BIDSA to support the continued improvement of business process and decision-making.

Firm A12 "….if my firm does not use BIDSA, it is difficult to enhance services to customers (e.g. using data mining for CRM) , however the firm should beware of selecting BI vendors that suit firm requirement"

In addition, this major group of factors related to the use of BIDSA was benefits, including compatibility as well as ease of use. Many managers reported that one of the benefits that the business organisation received was to typically relate to: 1) identification of information needs; 2) information acquisition; 3) information analysis; and 4) storage and utilisation.

Moreover, analytical tools are presenting complex internal and competitive information in term of good reports to managers or decision makers. All managers accepted that firms having these technologies are more sophisticated and have risk to implement (e.g. complexity). Then, most managers believed that these technology are easy and comfortable to use, and compatible with the work of ERP users. One-third of managers commented that these instruments assist managers to solve and find solutions at real-time.

Another group of factors was information technology governance and information technology support, more than half of the managers commented that architecture, infrastructure, business application need, and investment are important for using this technology. Firms needed to consider the frame work of IT governance in order to help design structures and processes that enhance their strategic use of IT including BIDSA.

In summary, all managers believed that the financial investments made in the adoption of BIDSA were cost effective. They felt that BIDSA is a useful tool to their firms from strategic to operating functions. Moreover, most of them felt that these technologies are ease of use and compatible with the work of firms and their employees. However, IS/IT knowledge and skill are required to these employees. Formal training should be provided during testing, implementing, and post implementing. Two managers mentioned that effective governance is a key to adopt and use data warehouse. Five managers reported that they use BI real-time application to generate tremendous opportunities and choices in the marketplace for firms and customers. It responds to market and customer demand in hours and in minutes not in weeks. Measuring and monitoring business activities (e.g. SCM, CRM) interactively to respond to timely decision are possible in real-time BI. In addition, all mangers expected to increase "ability to determine how to take action based on the results of BI analysis" in organisations.

APPENDIX A3

A3: QUESTIONNAIRE FOR CONDUCTING IN AUSTRALIA

(See the next page)

SURVEY QUESTIONNAIRES

"Business Intelligence and Decision Support Application (BIDSA)"

****Please Note****

This questionnaire will take approximately **5-10 minutes** to complete. Your answers will be treated with strictest confidence by **Victoria University** (*Melbourne, VICTORIA*) and used solely for this research project. No individual information will be forwarded to any external organisation.

This questionnaire is aimed at the person who makes a decision in the development of business intelligence (BI) systems in your organisation (e.g. *Director of Information Technology (IT) department or Chief Information Officer (CIO)*). I am aware you are busy, and I would be grateful if you could take the time to answer this questionnaire.

There are THREE parts of the survey questionnaire.

Definition

Business intelligence and Decision Support Application (BIDSA) is a series of information systems designed to support decision-making. These information systems are as sets of powerful tools assist to improve business executive decision making, business operations, and increasing value of the enterprise. **BI** basically requires three main categories of technology: 1) BI infrastructure (e.g. data warehouse, data mart); 2) CPM applications (BI analytical tools e.g. OLAP, data mining, other modelling); 3) BI reporting or presenting tools (e.g. web presentation, management reporting).

The use of conducting **BIDSA** is an organised and systematic process by which organisations acquire, analyse, and disseminate information from both internal and external information sources significant for their business activities and for presenting complex internal and competitive information to decision makers.

Definition of terms

BIDSA:	Business intelligence and decision support applications
BI:	Business Intelligence
IT:	Information technology
IS:	Information systems
DSS:	Decision support systems
EIS:	Executive information systems
KMS:	Knowledge management systems
OLAP:	On-line analytical processing
CPM:	Corporate performance management
ERP:	Enterprise resource planning
SCM:	Supply chain management
CRM:	Customer relationship management

SURVEY QUESTIONNAIRES

"Business Intelligence and Decision Support Applications"

Part I: Background Information

The questions asked in this section will be used for classification purposes only. The information gathered will not be used in any other way and be kept strictly confidential.

1. Date of completion of survey: Date (___) Month (__________) Year (_____)

2. Name of your organisation :
   ____

3. Industry type of your company?
   (   ) Manufacturing   (   ) Servicing   (   ) Others, please indicate _______________

4. How many full-time employees does this company employ? ____________

5. Your current position in this company: _______________________________

6. How long have you held your current position? ________ years

7. Please rate the level of **BIDSA** adoption in your company: (please place a checkmark **(X)** in the one bracket that is closest to your situation)
   (   ) Only basic IS (e.g. DSS, EIS, KMS)
   (   ) Only data warehouse (and/or data mart)
   (   ) Have data warehouse and analytics (e.g. OLAP, data mining)
   (   ) Have data warehouse, analytics, and strategic tools (e.g. SCM, CRM applications)
   (   ) Have all of them mentioned above with BI real-time
   (   ) Have none of them, please indicate
   ____

8. How long has your company used **BIDSA**? _____ years

9. How much have your company approximately spent for capital spending on **BIDSA**?

   ____

10. For adopting or implementing **BIDSA**, which vendors is your company relying on?
    (   ) SAP   (   ) SAS   (   ) Microsoft   (   ) Informatica
    (   ) Siebel   (   ) Cognos   (   ) Peoplesoft   (   ) Oracle
    (   ) others, please specify

    ____

11. How did you find out about how to use **BIDSA** in your organisation? (Irrespective of how much you know, you can refer to the range of sources that you have learned from: e.g. academic course, working in a company, vendor training, friends etc, and comment on their usefulness).

____

____

Part II: Factors Affecting the Adoption of BIDSA

Please indicate your level of agreement or disagreement with each of the following statements. For each statement below, please circle the number that best describes your view.

Level of agreement or disagreement **used for (PART II and III)**

7 = Strongly agree
6 = Agree
5 = Slightly Agree
4 = Neither disagree nor agree
3 = Slightly disagree
2 = Disagree
1 = Strongly disagree

1) Perceived Benefits of using BIDSA	**Strongly Disagree**			**Neither Disagree Nor Agree**			**Strongly Agree**
1. BIDSA will enable your company to reduce cost in the operations	1	2	3	4	5	6	7
2. BIDSA provides competitive information and improves decision-support operations.	1	2	3	4	5	6	7
3. The company believes BIDSA will accomplish tasks and enhance business strategies.	1	2	3	4	5	6	7
4. BIDSA can monitor problems and provide solutions at real-time.	1	2	3	4	5	6	7

2) Complexity of using BIDSA	**Strongly Disagree**			**Neither Disagree Nor Agree**			**Strongly Agree**
5. The process of developing (establishing) BIDSA is complicated	1	2	3	4	5	6	7
6. The operation of BIDSA is considerably to be complicated to implement and use within your firm	1	2	3	4	5	6	7
7. BIDSA is hard to learn	1	2	3	4	5	6	7
8. Integrating BIDSA into current work practices will be difficult	1	2	3	4	5	6	7
9. Considerable resistance exists within the firm toward implementation and use of BIDSA	1	2	3	4	5	6	7

3) Compatibility of using BIDSA	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
10. Using BIDSA fits well with how the company functions.	1	2	3	4	5	6	7
11. Using BIDSA is consistent our compatible firm's value and beliefs	1	2	3	4	5	6	7
12. BIDSA is compatible with the organization's IT infrastructure	1	2	3	4	5	6	7
13. The changes introduced by BIDSA are compatible with existing operating practices	1	2	3	4	5	6	7
14. The connection between BIDSA and data resources in the original computer is important	1	2	3	4	5	6	7

4) Top Management Support of using BIDSA	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
15. Top management supports the adoption of BIDSA	1	2	3	4	5	6	7
16. Top management has offered related resources for the development of BIDSA	1	2	3	4	5	6	7
17. Top management is aware of the benefits of BIDSA	1	2	3	4	5	6	7
18. Top management provides the cooperation to complete for BIDSA projects	1	2	3	4	5	6	7
19. Top management recognises and understands knowledge of BIDSA in order to actively encourages users to use BIDSA	1	2	3	4	5	6	7

5) Business Size (resources) of using BIDSA	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
20. The size of company has a major impact on BIDSA adoption	1	2	3	4	5	6	7
21. The firm has the technological resources to adopt BIDSA	1	2	3	4	5	6	7
22. The firm provide financial resources to adopt BIDSA	1	2	3	4	5	6	7
23. Other organisational resources (e.g. training, IS support, IT governance) helps to build up higher levels of BIDSA adoption	1	2	3	4	5	6	7
24. There are no difficulty in finding all necessary resources (e.g. funding, people, time) to implement BIDSA	1	2	3	4	5	6	7

6) Absorptive Capacity of using BIDSA	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
25. Key users of BIDSA are quite familiar with, have a vision, and understand what BIDSA can do for the company	1	2	3	4	5	6	7
26. Key users need extensive training to develop skills and understand and use BIDSA	1	2	3	4	5	6	7
27. There are hardly any major knowledge barriers in using BIDSA	1	2	3	4	5	6	7
28. Key users are technically knowledgeable in exploiting BIDSA capabilities	1	2	3	4	5	6	7
29. There is adequate level of understanding and technical sophistication on the BIDSA users	1	2	3	4	5	6	7

7) Internal Need of using BIDSA	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
30. BIDSA is needed to improve a timely responding time	1	2	3	4	5	6	7
31. The needs to service quality is important for BIDSA	1	2	3	4	5	6	7
32. The needs to have cost reducing are required to use BIDSA	1	2	3	4	5	6	7
33. BIDSA is needed to provide correct information	1	2	3	4	5	6	7
34. BIDSA can help in raising competitive advantages	1	2	3	4	5	6	7

8) Selection of Vendors of using BIDSA	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
35. The degree of competition in industrial environmental places pressures on the firm to adopt this IT	1	2	3	4	5	6	7
36. The firm needs to utilise BIDSA to maintain its competitiveness in the market	1	2	3	4	5	6	7
37. The degree of competition in the industrial environment is important to use BIDSA	1	2	3	4	5	6	7
38. It is a strategic necessity to use BIDSA	1	2	3	4	5	6	7
39. This is a universality of new technology	1	2	3	4	5	6	7

9) Business Size (resources) of using BIDSA	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
40. The vendors' reputation is important in selecting BIDSA partner	1	2	3	4	5	6	7
41.The relationship with customers is important	1	2	3	4	5	6	7
42. The successful experience possessed is important	1	2	3	4	5	6	7
43. The capability to plan and complete project is important	1	2	3	4	5	6	7
44. The technological competency of consultants is important	1	2	3	4	5	6	7

Part III: Information System Knowledge

1. Please indicate your highest level of education by using a checkmark **(X)**

( ) High school
( ) TAFE/ commercial college
( ) Bachelor's
( ) master's
( ) Doctorate's

Please indicate your levels of using **BIDSA** in your company by circling the number on the scale with each of the following statements:

Level of using BIDSA	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
2. Basic BIDSA (e.g. DSS, EIS, KMS)	1	2	3	4	5	6	7
3.Only data warehouse	1	2	3	4	5	6	7
4. Data warehouse and analytic tools (e.g. OLAP, data mining)	1	2	3	4	5	6	7
5. Data warehouse, analytics tools, and extended applications (e.g. CRM, SCM)	1	2	3	4	5	6	7
6. Data warehouse, analytic tools, extended applications, and BI real-time	1	2	3	4	5	6	7

Please indicate your level of understanding of how to use BIDSA by circling the number on the scale that best describes your view

Knowledge of using BIDSA	Strongly Disagree			Neither Disagree Nor Agree			Strongly Agree
7. I have a very good understanding of how to use BIDSA	1	2	3	4	5	6	7

"THANK YOU VERY MUCH FOR YOUR TIME AND COOPERATION"

Victoria University

APPENDIX A4

A4: LISTS OF DECISION SUPPORT TECHNOLOGIES USED IN YOUR COMPANY

Company No. (__________)

Company Name (____)

Contact Address and Phone (if possible)

____

____

Technology Categories	Technology Types	Yes/No	Remarks
Basic decision support characteristics	Personal DSS		
	Group Support Systems		
	EIS		
	KMS		
	Intelligent DSS		
	Others (Please indicate)		
BI Infrastructure	Data Warehouse		
	Extraction-Transaction-Loading		
	Data mart		
	Others (Please indicate)		
BI Analytics	On-line Analytical Processing		
	Data Mining		
	CPM (Corporate Performance Measurement)		
	Others (Please indicate)		
BI Extended Business Application	CRM		
	SCM		
	PLM (Product Lifecycle management)		
	SRM (Supplier Relationship Management)		
	Others (Please indicated)		
BI Real-Time Monitoring	BI Real-Time		
	Business Activity Monitoring		
	Others (Please indicate)		

Table A4-1: Summary of technological types of decision support characteristics

APPENDIX A5

A5: POTENTIAL FACTORS INFLUENCING ADOPTION OF ORGANIZATIONAL AND INFORMATION SYSTEMS AS A GUIDELINE

Categories of Factors	Factors	Yes/No	Remarks
System (Technology) characteristics	Relative Advantage		
	Compatibility		
	Complexity		
	Observability		
	Triability		
	Benefits		
	Cost		
	Barriers		
	Others (please indicate)		
Organizational Characteristics	Size		
	Employee IS knowledge		
	Information intensity		
	Financial costs		
	Support systems		
	Organizational readiness (Technological and Financial)		
	Availability of resources		
	Complexity of existing IT infrastructure		
	Top management support		
	Champions		
	Others (please indicate)		
Decision Maker Characteristics	Innovativeness		
	IS knowledge		
	Attitude		
	Age		
	Education		
	Others (please indicate)		
Environmental Characteristics	External influence		
	External pressure		
	Government pressure		
	Competitive intensity		
	Market uncertainty		
	Vendor selection		
	Environment instability		
	Others (please indicate)		

Table: A5-1: A guideline of potential factors influencing adoption of organizational and information systems

APPENDIX A6

A6: SURVEY COVERING LETTER FOR CONDUCTING IN AUSTRALIA

(See the next page)

FACULTY OF BUSINESS AND LAW

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15 May 2008

Dear Director of Information Technology Department/ Chief Information Officer,

I am currently carrying out research for the degree of Doctor of Philosophy (Ph.D.) through the **School of Management and Information Systems** at **Victoria University**, Melbourne, Australia. The aim of this study is to examine the use of business intelligence (BI) and decision support applications by Australian business organizations. The results will be very useful in developing and implementing successful BI systems.

I would like to invite you to be a part of my Ph.D. study into "Business Intelligence and Decision Support Applications" (BIDSA). Your assistance in this matter is much appreciated and will lead to a greater understanding of the use of "Business Intelligence and Decision Support Applications" and help us find out what could be recommended or improved for the Australian business sector.

For this purpose, questionnaire survey will be used for my research with the people who make a decision in developing BI and decision support applications. The information given by your company will be treated in strict confidence and will only be used for this study. Protecting the confidentiality of your answers is very important to me, as well as the University.

It would be greatly appreciated if you would kindly complete the attached questionnaire and return it in the prepaid reply envelope at your earliest convenience, preferably by **1 July 2008**. If you have any query regarding the research project, please feel free to contact me by e-mail at Singha.Chaveesuk@live.vu.edu.au or by phone # on 614 2256 9300 or my principal supervisor, Associate Professor Arthur Tatnall at **Arthur.Tatnall@vu.edu.au** or by phone # on 613 9919 1034

Thank you very much for your time and cooperation.

Yours Faithfully,

Singha Chaveesuk

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APPENDIX A7

A7: MISSING DATA ANALYSIS (Univariate Statistics)

	N	Mean	Std. Deviation	Missing		No. of Extremes	
				Count	Percent	High	Low
BEN1	149	5.25	1.572	1	.7	20	0
BEN2	150	4.77	1.420	0	.0	4	0
BEN3	150	4.78	1.678	0	.0	8	0
BEN4	150	4.77	1.429	0	.0	3	0
CPLEX1	150	4.73	1.510	0	.0	1	0
CPLEX2	150	4.65	1.475	0	.0	2	0
CPLEX3	149	4.52	1.427	1	.7	1	0
CPLEX4	147	4.50	1.528	3	2.0	0	0
CPLEX5	150	4.68	1.397	0	.0	2	0
CPAT1	150	4.94	1.480	0	.0	5	0
CPAT2	150	4.96	1.497	0	.0	5	0
CPAT3	150	4.76	1.658	0	.0	8	0
CPAT4	150	4.61	1.447	0	.0	3	0
CPAT5	150	4.80	1.381	0	.0	3	0
TOPMS1	150	4.41	1.659	0	.0	0	0
TOPMS2	150	4.67	1.579	0	.0	4	0
TOPMS3	150	4.45	1.422	0	.0	14	11
TOPMS4	149	4.17	1.472	1	.7	0	0
TOPMS5	150	4.35	1.563	0	.0	0	0
OSIZE1	150	4.39	1.528	0	.0	0	0
OSIZE2	149	4.29	1.406	1	.7	0	0
OSIZE3	148	4.47	1.363	2	1.3	0	0
OSIZE4	150	4.17	1.599	0	.0	0	0
OSIZE5	148	4.51	1.436	2	1.3	0	0
ABSORP1	150	4.55	1.417	0	.0	16	12
ABSORP2	150	4.49	1.514	0	.0	5	0
ABSORP3	150	4.60	1.601	0	.0	0	0
ABSORP4	150	3.97	1.472	0	.0	0	0
ABSORP5	149	4.75	1.423	1	.7	3	0
NEED1	149	4.67	1.495	1	.7	2	0
NEED2	150	4.89	1.489	0	.0	4	0
NEED3	150	4.73	1.464	0	.0	2	0
NEED4	148	4.45	1.477	2	1.3	0	0
NEED5	149	4.73	1.478	1	.7	2	0
CPET1	145	4.18	1.588	5	3.3	0	0
CPET2	149	4.46	1.806	1	.7	0	0

CPET3	150	4.33	1.574	0	.0	0	0
CPET4	147	4.27	1.536	3	2.0	23	11
CPET5	150	4.23	1.255	0	.0	0	0
VEND1	148	5.03	1.532	2	1.3	5	0
VEND2	149	5.02	1.522	1	.7	3	0
VEND3	148	4.69	1.573	2	1.3	4	0
VEND4	145	4.56	1.585	5	3.3	2	0
VEND5	148	4.78	1.586	2	1.3	3	0
ADOPT1	147	4.42	1.404	3	2.0	13	10
ADOPT2	149	4.58	1.198	1	.7	10	8
ADOPT3	149	3.81	1.637	1	.7	0	0
ADOPT4	147	3.18	1.688	3	2.0	0	5
ADOPT5	150	4.31	1.461	0	.0	23	3

Table A7-1: Summary of missing data

APPENDIX A8

A8: CORRELATIONS AND STANDARDISED RESIDUAL COVARIANCE FOR INVESTIGATING DISCRIMINANT VALIDITY

	MT10	MT9	MT14	MT8	MT11	MT13	MT5	MT6.	MT7	MT1	MT2	MT3	MT4
MT10	1.000												
MT9	.376	1.000											
MT14	.580	.304	1.000										
MT8	.333	.521	.269	1.000									
MT11	.695	.363	.562	.322	1.000								
MT13	.516	.270	.417	.239	.499	1.000							
MT5	.470	.735	.380	.652	.455	.337	1.000						
MT6	.361	.565	.292	.501	.350	.260	.707	1.000					
MT7	.379	.593	.306	.525	.367	.272	.741	.570	1.000				
MT1	.335	.238	.271	.211	.324	.241	.297	.229	.240	1.000			
MT2	.304	.216	.246	.191	.295	.219	.270	.208	.218	.608	1.000		
MT3	.317	.225	.256	.199	.307	.228	.281	.216	.227	.632	.574	1.000	
MT4	.273	.193	.221	.172	.264	.196	.242	.186	.195	.544	.494	.514	1.000

Table A8-1: Correlations of indicators for "technological innovation" as exogenous latent constructs

	MT14	MT8	MT11	MT13	MT6	MT7	MT2	MT3	MT4
MT14	.000								
MT8	-.545	.000							
MT11	-.010	-.953	.000						
MT13	.148	.442	-.029	.000					
MT6	.303	.388	-.387	-.773	.000				
MT7	1.013	-.100	.649	-.040	-.126	.000			
MT2	-1.005	-.575	-1.084	-.704	-.148	-.412	.000		
MT3	-.189	.416	-.018	.432	-.818	-.214	.599	.000	
MT4	-.263	.645	1.326	.335	-.125	.775	-.018	-.520	.000

Table A8-2: Standardised residual covariances of variables for "technological innovation" as exogenous latent constructs

	MO6	MO1	MO10	MO9	MO20	MO15	MO14	MO8	MO16	MO17	MO19	…
MO6	1.000											
MO1	.306	1.000										
MO10	.571	.322	1.000									
MO9	.418	.236	.441	1.000								
MO20	.243	.195	.256	.187	1.000							
MO15	.151	.131	.159	.117	.126	1.000						
MO14	.132	.115	.139	.102	.110	.512	1.000					
MO8	.456	.257	.481	.352	.204	.127	.111	1.000				
MO16	.215	.173	.227	.166	.570	.112	.098	.181	1.000			
MO17	.211	.170	.223	.163	.561	.110	.096	.178	.497	1.000		
MO19	.154	.124	.162	.119	.408	.080	.070	.130	.362	.356	1.000	
MO11	.158	.137	.166	.122	.132	.613	.535	.133	.117	.115	.084	
MO12	.131	.114	.138	.101	.110	.511	.446	.111	.097	.096	.070	
MO13	.161	.140	.170	.124	.135	.627	.547	.136	.119	.117	.086	
MO7	.536	.302	.565	.414	.240	.149	.130	.451	.213	.209	.152	
MO2	.288	.548	.303	.222	.184	.124	.108	.242	.163	.160	.117	
MO3	.302	.574	.318	.233	.193	.130	.113	.254	.171	.168	.122	
MO4	.303	.577	.320	.234	.194	.130	.114	.255	.172	.169	.123	
MO5	.332	.631	.349	.256	.212	.143	.124	.279	.188	.185	.134	…

…	MO11	MO12	MO13	MO7	MO2	MO3	MO4	MO5
…								
…								
MO11	1.000							
MO12	.533	1.000						
MO13	.654	.545	1.000					
MO7	.156	.130	.159	1.000				
MO2	.129	.108	.132	.285	1.000			
MO3	.135	.113	.138	.299	.541	1.000		
MO4	.136	.113	.139	.300	.544	.570	1.000	
MO5	.149	.124	.152	.328	.594	.623	.626	1.000

Table A8-3: Correlations of indicators for "<u>organization</u>" as exogenous latent constructs

	MO14	MO10	MO8	MO16	MO17	MO19	MO12	MO13	MO7	MO2	MO4	MO5
MO14	.000											
MO10	-.329	.000										
MO8	.135	.071	.000									
MO16	-.703	-1.142	-.318	.000								
MO17	-1.178	-.101	-.293	.428	.000							
MO19	1.497	.490	.678	-.151	-.342	.000						
MO12	-.170	.110	.693	-.592	1.638	.616	.000					
MO13	.109	-.626	1.228	-.969	-.267	.653	-.025	.000				
MO7	-.249	.125	-.489	-.229	.776	1.105	1.495	-.487	.000			
MO2	.078	-.849	-.237	-.600	.481	1.551	1.351	-1.335	-.699	.000		
MO4	1.450	-.361	-.647	-.329	-1.043	1.684	-.046	-.657	-1.074	.444	.000	
MO5	1.193	.223	1.134	-.544	-.779	1.040	.596	-.198	.996	-.121	-.085	.000

Table A8-4: Standardised residual covariances of variables for "<u>organization</u>" as exogenous latent constructs

	ME9	ME2	ME1	ME6	ME7	ME8	ME10	ME3	ME4	ME5
ME9	1.000									
ME2	.257	1.000								
ME1	.217	.604	1.000							
ME6	.485	.250	.211	1.000						
ME7	.599	.308	.260	.583	1.000					
ME8	.550	.283	.239	.535	.661	1.000				
ME10	.614	.317	.267	.598	.738	.678	1.000			
ME3	.234	.652	.550	.228	.281	.258	.289	1.000		
ME4	.256	.712	.601	.249	.307	.282	.315	.649	1.000	
ME5	.210	.586	.495	.205	.253	.232	.259	.534	.583	1.000

Table A8-5: Correlations of indicators for "environment" as exogenous latent constructs

	ME2	**ME6**	**ME7**	**ME8**	**ME10**	**ME4**	**ME5**
ME2	.000						
ME6	.722	.000					
ME7	.665	.129	.000				
ME8	.411	-.235	.042	.000			
ME10	1.277	-.021	-.102	.118	.000		
ME4	.030	-.657	-.816	-.659	.224	.000	
ME5	-.263	.829	.570	-.443	.874	.085	.000

Table A8-6: Standardised residual covariances of variables for "environment" as exogenous latent constructs