Business Intelligence usage determinants: an assessment of factors influencing individual intentions to use a Business Intelligence system within a financial firm in South Africa

Name: Deane Nkuna

Student Number: 9411618M

University of Witwatersrand

Supervisor: Jean-Marie Bancilhon

December 2011

Submitted in 50% fulfilment of the requirements for a Master's degree in Commerce (Information Systems)

DECLARATION

I declare that this research is my own work and has not been submitted to any institution for either academic or non-academic purpose. It is submitted for the first time to the school of business and economic sciences at the University of Witwatersrand towards a Masters degree in Information Systems.

Signed__________________

Deane Nkuna
0824988470
December 2011

ACKNOWLEDGEMENTS

Thanks are due to my supervisor, Jean-Marie Bancilhon, for his guidance throughout the research process. My gratitude also goes to those staff members in the Department of Information Systems at the University (between January 2010 and December 2011) whom I have had personal encounters with, and those who directly contributed to the completion of this project. Last, but not least, I thank God my Creator, my parents, and my wife and children for tapping my back when it was timely to do so.

ABSTRACT

Although studies are conducted on economical gains due to BI system adoption, limited knowledge is available on factors which influence BI system usage. Identifying these factors is necessary for organisations because this may enable the design of effective BI systems, thus increasing the chance of firms adopting them to realise the actual value inherent in the exploitation of BI systems. The purpose of this study is, therefore, to investigate factors which influence BI system usage. The investigation employed constructs derived from three theoretical frameworks, namely technology acceptance model (TAM), task-technology fit (TTF) and social cognitive theory (SCT) as follows: intention to use, perceived usefulness, perceived ease use, task characteristics, technology characteristics, task-technology fit and computer self-efficacy. To test the hypotheses, data was collected by administering the study to 682 BI system users in a South African financial institution, SA-Bank, wherein 193 usable responses were received. The findings of the study with partial least squares (PLS) analysis indicated support for the joint use of constructs from the three theoretical frameworks, explaining 65% of BI system usage variance. Furthermore, the perceived usefulness of a BI system reflected a stronger influence as a factor of BI system usage over the beliefs that the system was easy to use, and the belief that it was aligned to the performance of business tasks. An unusual outcome in this study was the lack of influence of computer self-efficacy on BI system usage. Nonetheless, the study extended validation of the use of constructs derived from the three theoretical frameworks for a BI technology in the context of SA-Bank, thereby contributing to theory. Finally, the results of hypothesis testing suggested a starting point for practitioners towards designing BI systems, and recommendations and suggestions are included in this report.

Keywords: decision task characteristics, BI system characteristics, decision task – BI system fit, computer self-efficacy, perceived usefulness, perceived ease of use, intention to use.

Table of Contents

List of figures

List of tables

DEFINITION OF TERMS

- ***BI analytics*:** a term for the collective mathematical operations performed on data which resides in the data warehouse
- ***Convergent validity*:** Is the check to determine whether indicators theoretically declared to measure a construct, significantly measure that construct.
- ***Decision maker(s)*:** refers to a person who is involved with handling decision tasks, used interchangeably in this study with ***BI user*.**
- ***Decision support systems (DSS)*:** A class of systems which are used for organisational decision support. Business intelligence serves as an example of DSS.
- ***Decision task*:** a task which its execution depends on information processing that is aided by a BI system (or a DSS).
- ***Discriminant validity*:** Is the check to determine whether indicators theoretically declared to measure a construct, significantly measure another construct of the same research model.
- ***Kurtosis*:** This refers to the measure of the height of the bell-shaped curve. Kurtosis is assigned a value of zero if the height of the bell shaped curve is normal, otherwise it is assigned either a negative or positive value depending on the direction of the abnormality.
- ***Measurement model*:** A model that enables the measurement of the reliability of indicators making a construct.
- ***Normal distribution (data normality)*:** The distribution of data such that when plotted on a graph, reproduces the popular bell-shaped curve in statistics.
- ***Outlier*:** A case that deviates from the predominant observation of data gathered to be analysed.
- ***Skewness*:** The measure of symmetry of the bell shaped curve. If symmetrical, then skewness is zero, otherwise it is assigned a positive or negative value depending on the direction of this abnormality.

- ***Structural equation modelling (SEM)*:** A multi-variate technique that determines simultaneously the significance of relationships among model constructs, and the significance of relationships of individual constructs and their respective items.

CHAPTER 1: INTRODUCTION

1.1 Overview

This chapter introduces the study of business intelligence factors which influence usage within a financial organisation in South Africa (SA), SA-Bank. SA-Bank implemented a business intelligence (BI) system that lived up to the expectations of the managers behind this initiative, and thus serves as an appropriate context for the purpose of the study. BI is one of the latest innovations dominating information technology (IT) investments made by businesses (Lawton, 2006 & Negash, 2004). It is acclaimed to be a perfect strategic initiative by some of the organisations who have adopted it (Phan and Vogel (2009; Petrini and Pozzebon, 2009; Ramamurthy, Sen and Sihna, 2008 & Watson, Wixom, Hoffer, Anderson-Lehman and Reynolds, 2006), although not with fewer challenges when contrasted to related innovations which came before its existence. For instance, literature on enterprise resource planning systems, another innovation in its day, is made of varying views surrounding its implementation. Some studies like Bernroider (2008) suggest enterprise performance enhancement through using enterprise resource planning solutions, while others like Galliers and Newell (2003) indicate performance reduction of common approaches to their implementation. One major difference between BI and such long existing technologies is the deficiency of formalised knowledge around BI (Petrini and Pozzebon, 2009; Lawton, 2006 & Lönnqvist and Pirttimäki, 2006). As a concept, it lacks a universal definition and a formal approach towards implementation. The available knowledge on BI appears insufficient to serve as reference to practitioners towards effective design of the innovation within firms. The study therefore aims to advance knowledge on the design of BI applications. This is achieved through the assessment of factors proposed in this study to be determinants of business intelligence system usage.

The chapter begins with a discussion of BI as a concept, definition, its origination and current trends. It then proceeds to explain the context in which the study is performed, its importance to practitioners and academia, aims and objectives, the scope, and ends with a conclusion and the structure of the study.

1.2 Business intelligence and current trends

There are overlapping definitions between BI and data warehousing, a concept it strongly relates to. Distinguishing between the two is necessary in building towards a clear definition of BI. It is a cliché to say that the two concepts are related, even though it is unclear how they actually relate. A data warehouse (DWH) is defined as an integrated data store upon which tools that manipulate data can be used towards decision support (Dayal, Castellanos, Simitsis, Wilkinson, 2009). BI is defined as a software tool for gathering, integrating and analysing data from the different data sources of a business enterprise towards decision support (Phan and Vogel, 2009 & Golfarelli, Rizzi and Cella, 2004). The definitions make it clear that BI comprises a data warehouse and reporting tools which are used for data processing and manipulation. Petrini and Pozzebon (2009) define BI as a strategy enabler, that is, a tool which can be used to integrate information from all strategic areas of a business enterprise. It is thus defined in this study as a strategic information system which supports organisational decision making from an integrated data store.

The term 'business intelligence' was coined by Howard Dressner of Gartner in the early 90's (Watson and Wixom, 2007). BI has gained popularity as a tool used to track performance of business processes and of transactional systems. Through a BI system, information generated from all business activity is integrated and made accessible to strategy personnel towards business performance tracking and enhancement (Phan and Vogel, 2009 & Petrini and Pozzebon, 2009). Current trends also indicate that BI systems can be employed for varying purposes, and thus can be named according to the needs for which they are adopted. The most predominant terms widely used by BI practitioners are: business performance management, real-time business intelligence and pervasive business intelligence (Watson and Wixom, 2007 & Lawton, 2006). Business performance management refers to a BI system that enables gathering of statistics about business processes, preparation and presentation of such data as input to organisational performance analysis (Kim and Kankanhalli, 2009). Real-time BI systems are applied in environments where trend analysis of current business transactions is mandatory for decision support (Watson, *et al.*, 2006). Lastly, pervasive BI system are designed to enable a firm share decision support functions with its strategic partners (such as suppliers and joint venture partners) also in the process enabling such an organisation to tap into external data sources towards decision support (Lawton, 2006).

The forms of BI applications defined above, although promising to match the information needs of businesses, are described within the IS literature with little information as to how practitioners could build them such that they are used. This emphasises the need for a study which advance BI knowledge on factors affecting its design. SA-Bank appeared a suitable context for such an investigation to be carried, because it was employing services of a BI system that was popular among the employees of this firm. The context of SA-Bank is outlined as the next section of this chapter.

1.3 Context of study

SA-Bank is a forty year old financial institution situated in South Africa. It specialises in mobile asset financing such as cars, trucks, construction machinery and aeroplanes. According to information kept in its intranet, it is a market leader in the business space of automobile financing, which they define as asset financing. One of its core businesses is passenger car sales, where individuals apply for loans to purchase cars from manufacturers through car dealers. This line of business is supported by a business process, which is related to most of the business activity happening at SA-Bank. Manufacturers have formed joint ventures with SA-Bank in agreements which shift administrative responsibility for car sales to SA-Bank. For instance, a customer intending to buy a Toyota brand from a car dealer, supplies information to SA-Bank for credit approval assessment instead of sending it to the Toyota manufacturer. Thus communication channels are established between SA-Bank and its partners, such that information flow for passenger car sales is seamless between car dealers and the firm. The BI system (referred to within the firm as the BI portal) at SA-Bank is mainly used for data analysis generated from the business activity of this process. Although support for other processes is also happening, it is not as intensive as for the process referred to here. Access to the BI system is also granted to SA-Bank partners, enabling them to view business trends within the firm that are applicable to their respective businesses.

1.4 The need for this study

Lawton (2006) states that BI systems only add value when they are used by the people for whom they are built. The value, however, is only generated once these users have interpreted data and information towards decision support. Therefore, determining factors which lead to BI usage is important towards ensuring that users get applications that are relevant to their needs. As an example, Zhong, Liu and Yao (2007) have found that a dashboard, i.e. a graphical web interface through which data is presented to users, can limit users from fully exploiting web based intelligence with the choice of layout that display data to users. This example emphasises how useful it is to know about the factors which are likely to motivate users to use a computer application prior to its implementation. In addition, Benroider (2008) argues that if proper standards towards IT implementation are established, adoption becomes less demanding both in cost and effort. The ultimate goal for practitioners is to develop and implement BI systems that are useful towards helping users solve decision problems, and do so in a cost effective manner. Given that BI system usage is voluntary, a challenge is raised to BI practitioners to convince decision makers that it is worth using BI systems. More importantly, is the fact that usage is necessary towards realising the value of a BI innovation. This is suggested by DeLone and Mclean's (1995) model of information system success which shows that technology usage precedes benefits.

Ramamurthy *et al*. (2008) found that the environment in which a computer application is implemented also affects user behaviour towards the system. They further suggested that different environments are likely to influence user perceptions of the same technology differently. This suggests that there could be environmental issues that are specific to the SA-Bank setting, especially where BI system usage is concerned. Thus, the current context extends the range of contexts investigated in IS research, implying knowledge is also advanced in terms of factors arising specifically from the setting wherein the BI technology is applied.

1.5 Research aims

The aim of the study is to determine factors which influence the usage of a business intelligence system within a banking institution in South Africa. Analysis is performed in three areas within this context. The first area, which is the BI application, analysis is performed in order to determine factors influencing usage arising from system attributes. The second area is the work activity for which the system is used, that is, decision tasks. These (decision tasks) are analysed for characteristics which influence BI system usage. Finally, BI users are assessed for capability in relation to BI usage. Thus the aim is to assess the effect of system, decision task and user capability characteristics on BI system usage.

1.5.1 Research objectives

The main question that the research answers is: How do the system, decision task, and user capability characteristics impact on BI system usage? In order to answer this main question, the research is broken down into research objectives presented as sub-questions below:

1 What are the combined decision task and BI system characteristics that lead to BI system usage?

2 What are the capability beliefs that influence BI system usage?

3 What are the beliefs that influence decision makers to use a BI system?

Question 1 focuses on the assessment of user perceptions on the combined effect of the BI system and decision task characteristics on usage. The objective aimed at by this question was motivated by most users at SA-Bank relying on decision support systems to complete their business activity, hinting that the BI system should be investigated in light of decision tasks that are processed by users. Therefore, analysis of the combined effect of the BI system and a decision task on usage aligns with the observed BI user behaviour at SA-Bank. For this purpose Goodhue and Thompson (1995) suggested a model they termed, task-technology fit, which measures the combined effect of task and IT system characteristics on technology utilisation. Task technology fit suggests that a technology will be used only if it is aligned to the needs of the task to be executed. Thus it may be appropriate to answer this question of the study.

Question 2 seeks to determine characteristics of individual user capability that influence the use of a BI system. Lawton (2006) views users to be an integral part of an organisation's BI initiative. Users interpret data and information generated and distributed by the BI system to service decision task needs. Through interpretation they create value from the data and information generated with the use of a BI system. Therefore, the inclusion of user capability in BI system usage determinant analysis is inevitable. User capability quality is measured with the computer self-efficacy scale adapted from Compeau and Higgins (1995). Computer self-efficacy is defined by these authors as one's perceived capability to use a computer system. Hsu and Chiu (2004) stated that computer self-efficacy does not measure the skills which a person has, but the perception of whether one is able to apply the skills to use a computer. This aspect of computer self-efficacy makes it even more suitable for the intended analysis of individual users in this study, because it enables capture of the belief of capability to use a BI system and not a specific BI skill. Given that there is a wide variety of computer skills at SA-Bank, the intention was therefore not to measure these varying skills, but how users irrespective of what they know interact with the BI system.

The last objective likely to be achieved by an answer to question 3, determines user beliefs influencing BI system usage. The inclusion of user beliefs as determinants of a BI system usage is supported by Vessey and Galletta (1991) who suggested that technology usage depends on a user forming a mental view of whether applying it assists with problem solving or not. This also boded well with studying a technology that was non-mandatory, that is, where the only factor motivating usage was the user perceived reward that is inherent in applying the technology when executing decision tasks. Two user beliefs, perceived ease of use (PEOU) and perceived usefulness (PU), found to affect IT system use by Davis (1989) were adopted for this study. These two belief constructs form part of the technology acceptance model (TAM), which suggests that an IT application will be used based on the belief that it is useful and it is easy to use (Venkatesh and Davis, 2000). In this study these belief constructs present a measure of the mental view that a user forms about the BI system as a decision aid, taking into account his/her ability to operate the BI system, and the match between decision tasks and BI system characteristics.

1.6 Delimitations

This study analysed operational decision tasks, which are defined in this study to be tasks that are executed by any user who is not a senior manager. For example, credit personnel drew statistics that enabled them complete tasks related to bad-debts and credit risk trends, call-centre managers depend on statistical data to be able to manage workforce and team-agent performance. Ideally, analysis of decision tasks would be performed for only managerial activity because that is where strategic decision making happens (Chan and Huff, 1992). The current study, however, does not focus on the analysis of these tasks due to the small number of users at this level in SA-Bank.

1.7 Conclusion and structure of the study

The chapter gives a background of business intelligence technology and the purpose of the study, which is assessment of BI system usage determinants. It also introduces the context in which the study is performed, the aims and objectives of the study, and the description of the scope of study. The rest of the study is made up of the following chapters:

- *Chapter Two – Literature review*

  The model upon which the study is based is developed, and the theories are discussed in detail.

- *Chapter Three – Methodology*

  The sampling method and methods used to gather and analyse the data are discussed.

- *Chapter Four – Data analysis*

  The data is analysed using statistical rigor adapted from past information system studies.

- *Chapter Five – Findings and discussion*

  Inferences are drawn based on the data analysis, aims and objectives of the study.

- *Chapter Six – Conclusion*

  Conclusions to the aims of the research, the limitations of the research, emerging limitations during data gathering and analysis are discussed together with future research suggestions in light of the studied IS phenomenon.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview

This chapter outlines the theoretical basis for the study of business intelligence system usage determinants. It begins with a discussion of the dependent variable of the study, explaining it from the various perspectives given in existing BI literature. This is done in order to isolate the kind of usage focused upon in this study from other kinds of BI system usage. The discussion of this chapter also covers in detail the theoretical frameworks, task-technology fit, technology acceptance, and the construct, computer self-efficacy, applied jointly to form a measurement instrument for the purpose of this study. Furthermore, the relationships between the proposed determinants as measured by the instrument are discussed, leading to the formulation of hypotheses to be tested in this study. This chapter culminated in the identification of measurement items from past studies (Gefen, Straub and Boudreau, 2000), which were used in scales that measure the concepts introduced in this chapter (see Appendix A).

2.2 BI usage views

BI usage takes various forms depending on the objectives that an organisation sets to achieve through its BI system (Vandenbosch and Huff, 1997). It is mainly used to analyse internal business data and information that is generated from operational activity, for the purposes of: business process monitoring, customer relationship management and business strategy monitoring and evaluation (Negash, 2004; Phan and Vogel, 2009; Leidener and Elam, 1995; Wixom, 2004 & Xu, Kaye and Duan, 2003). BI can also be used to analyse threats and opportunities through using data and information from the external environment in which an organisation operates (Rouibah and Ould-ali, 2002), or from merged data of both the external and the internal environments (Lönnqvist and Pirttimäki, 2006).

Elbashir, Collier and Davern (2008) discuss two types of BI usage, evaluative and diagnostic, and further define these terms as briefly explained here. Evaluative usage is the utilisation of a BI system by a firm in order to determine whether organisational performance levels match the target of performance projected by strategic decision makers. Diagnostic usage is about user interaction with a BI system to draw information towards identifying causes to operational events. There are two usage patterns, however, that emerge from most of the existing BI studies. BI systems either emerges as tactically oriented (Negash, 2004; Watson and Wixom, 2007; Bowman, 2002), or as tools for strategy development and enhancement (Chen, Soliman, Mao and Frolick, 2000; Little and Gibson, 2003; Lönnqvist and Pirttimäki, 2006 & Vandenbosch and Huff, 1997). In the tactical usage pattern, referred to as tactical usage, BI is used to monitor and adjust operational activity from the analysis of business data as they are generated from business transactions. One good example of such usage can be found in Watson, *et al*.'s (2006) study of real time intelligence at Continental Airlines, where BI is used to manage information related to flight movement, such as plane delays and boarding gate problems as and when captured in transactional systems. The other usage pattern, referred to as strategic usage, relates to management usage of data and information to act on strategy development and organisational planning (Lönnqvist and Pirttimäki, 2006). There is however a connection between tactical BI usage as observed from BI literature, and diagnostic usage as defined by Elbashir *et al.* (2008). They are both linked to operational activity. They, however, differ in that tactical usage means supporting decision actions based on the analyses of current data (Lawton, 2006 & Watson and Wixom, 2007), while diagnostic usage analyses historical data (Elbashir *et al.*, 2008).

Similar to tactical and diagnostic usages, there is a connection between strategic and evaluative usage. They are both linked to senior management assessment of overall business activity. Strategic usage, however, relies more on historical data (Negash, 2004), while evaluative usage as defined above is reviewing business performance (effected with the analysis of current data) in comparison with a preferred state of performance that was projected by managers (or strategic personnel). Figure 1 summarises this categorisation. Tactical usage located in the bottom left corner of Figure 1 reflects that this form of BI usage relies on current data and is performed mainly by low level (operational) employees. This can be usage associated with operational performance adjustment, which users are able to achieve through the analysis of BI data and information recently generated from business transactions. Moving horizontally from tactical usage in Figure 1 above is diagnostic usage. In this type of usage, users are interested in finding out about causes to events in business transactions at the operational level. Users derive trends on historical activity in order to support decisions related to business process performance.

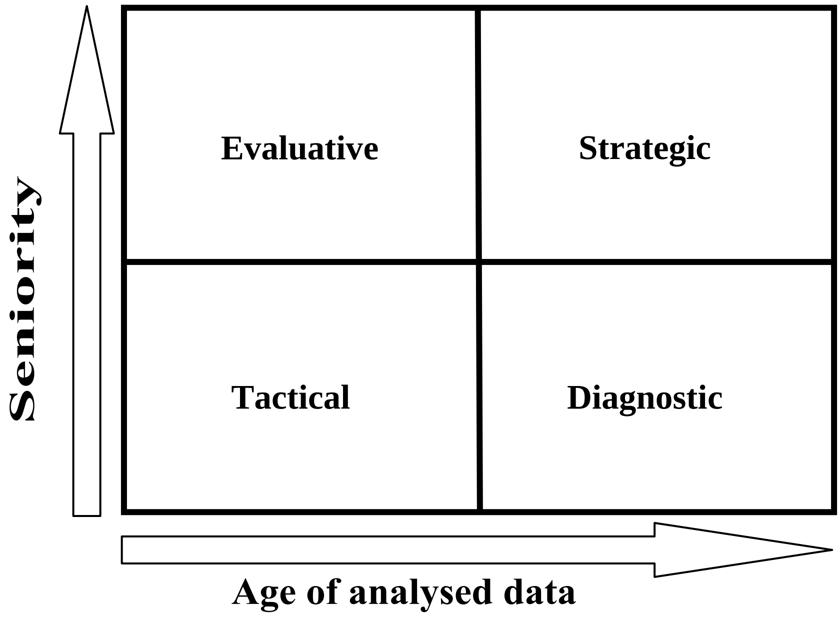


Figure 1: BI usage categories

Although Elbashir *et al.* (2008) view diagnostic usage as a managerial responsibility, it is suggested in this study that unless operational activity trends are interpreted in a language understood by senior management, they will be less meaningful to them, and thus this usage remains a low level (or non-managerial) activity. Diagnostic usage is thus the interaction of decision makers with the BI system at low level, but by decision makers who are more interested in historical data. Also depicted in Figure 1 is evaluative usage shown to depend on real-time data, and to be an activity performed by senior employees of a firm. Finally, strategic usage appears to be a usage type that is dependent on historical data, because high level users (or senior managers) are likely to analyse data that span time and space, because of the focus of their roles on strategy formulation.

It is important to note that one BI application can be classed in all the usage categories described in Figure 1, but what makes a difference in BI usage types is who uses the system, and what data from it is of interest to them. An answer to who uses a BI system will help to identify the level of usage, that is, whether it is senior organisational employees or operational employees. What data are of interest to users, will further help to identify the exact quadrant(s) of usage (as per Figure 1) in which a firm belongs.

2.2.1 *Usage at SA-Bank*

SA-Bank employs its BI system for two purposes, diagnostic and strategic usages. Diagnostic usage at this firm is seen from the predominant usage of the BI system by low level users. Mainly credit risk assessment employees rely on BI statistics to perform their daily duties. These users draw statistics to assess whether current credit approval processes are effective, or need enhancement. On the other hand, for customer relationship management, which is achieved through a call-centre setup at SA-Bank, team leaders use BI statistics for business activities such as monitoring call handling of call agents, and planning of the distribution of call-agents across responsibilities. Another source of evidence of a diagnostic BI system at SA-Bank is the age of data that is used for BI analytics. Data kept in the SA-Bank data warehouse (DWH) is all data generated from business activity exclusive of data generated on the current day. For example, users interacting with the BI system on any day, see all data of past transactions except transactions that are processed on that day. In addition to diagnostic usage, SA-Bank employs its BI system for strategic usage as well. This is evident on the interest that executives within the firm have in the BI system. Executive users are interested in high level summaries of data. To recap, SA-Bank seems to have few users at this level, since a large component of users is made up of users who are performing diagnostic type usage.

2.2.2 *BI usage in this study*

The study focuses on BI usage as a diagnostic usage type. The choice is influenced by the number of users in the chosen category at SA-Bank. In this category at the firm, users are numerous enough to make up the statistical thresholds required for data analysis (more details on this topic are covered in Chapter Three). On the same note, the number of strategic BI users cannot meet the minimum size requirement for quantitative IS research. The next section covers the theoretical frameworks from which constructs that are used to measure determinants of BI system usage are derived.

2.3 Theoretical background

2.3.1 Task technology fit model

According to Goodhue (1998), the task technology fit model was developed to gather user evaluations on IS performance. The task-technology fit (TTF) is defined as the combined effect of task and technology features on the usage of a technology (Goodhue and Thompson, 1995). The combined effect, determines whether an information system will be used or not. If a match of the task to be executed through a technology and the features of the technology is perceived to exist by users, it implies that a fit exists and thus that the technology is likely to be used (Zigurs and Buckland, 1998). On the other hand, if a match is hardly perceived to exist between the task and the technology, it means that there is a misfit between the two and the likelihood is that the technology is not going to be used. The TTF model therefore measures the task and technology characteristics in order to determine a set of these characteristics that result in usage of technology.

TTF has been tested in various contexts and for different information systems (Lin and Huang, 2008; D'Ambra and Rice, 2001 & Goodhue, 1998) and has so far stood the test of time. There are some views, however, that oppose the views of its current success in IS. The model is discussed by DeSanctis and Poole (1994) to have measurement limits. In their study, these authors show that TTF assumes that the effects of the environment in which a technology is used, remain the same across all contexts. The same view is shared by Dennis, Wixom and Vandenberg (2001) who emphasise that social effects should be incorporated in this model to correct for the disregard of context. With this limitation not taken for granted, in this study the measurement model of TTF that was developed by Goodhue and Thompson (1995) is adopted with additional theories, which promise to mitigate this incapacity of the model. TTF usage in this study is backed by the evidence that it has so far proven to be a valid measure specifically in the category of information systems, decision support systems, which BI belongs to (Lee, Cheng and Cheng, 2007; D'Ambra and Rice, 2001 & Lin and Huang, 2008).

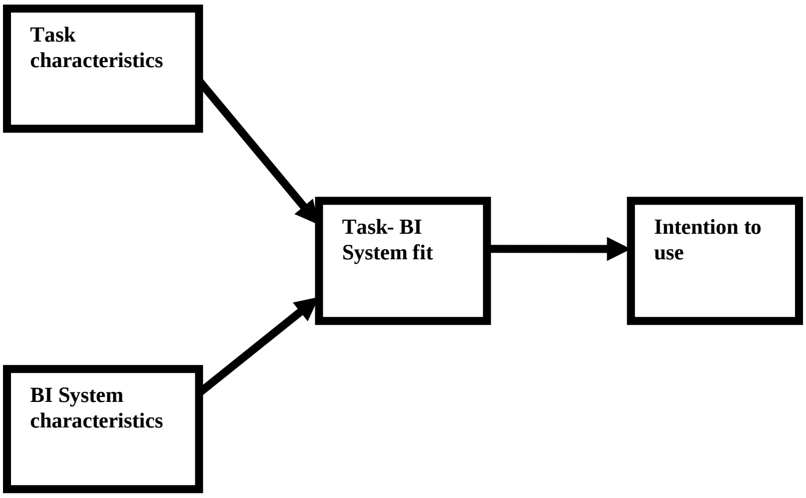


Figure 2 : A model of TTF adapted from Dishaw and Strong (1999)

A graphical depiction of the TTF model adapted from Dishaw and Strong (1999) is shown in Figure 2. This figure simply shows the variables for which this model enable analysis at SA-Bank, that is, qualities of decision tasks that are executed with the BI system, the BI system qualities and the user perception of fit in light of these two sets of qualities. The ultimate objective of performing this analysis is to determine how the user perception of fit between decision tasks and BI system qualities influences BI system usage at SA-Bank.

2.3.2 Computer self-efficacy

Computer self-efficacy (CSE) is defined to be a belief which a user has in his/her ability to execute a task with a computer system (Compeau, Higgins and Huff, 1999 & Compeau and Higgins, 1995). CSE, a construct derived from social cognitive theory (SCT) (Compeau, Higgins and Huff, 1999), was created to measure what one can do with the skill one possesses, and does not measure the exact skill possessed (Hsu and Chiu, 2004). An illustration also given in Compeau and Higgins (1995) is by an analogy of a driving skill and the driving process. In this analogy a driving skill and the driving process are differentiated by the fact that different people with the same driving skill could engage in the driving process of a motor car differently. How the brakes, accelerator and the steering-wheel are used among others could be jointly used to describe the driving process. Although the same driving skill could be possessed by different drivers, examining the driving process for the different drivers could lead to different outcomes. Similar to this analogy, the same computer skill can be possessed by different people, but their approach to the execution of tasks with a computer program could be different. Thus CSE measures the characteristics of the perceived ability to execute tasks given a specific computer program, a time saving measure to study users who possess numerous computer skills as observed at SA-Bank.

At SA-Bank, users possess computer skills such as skills for operating Microsoft windows platform, operating online communication tools and internet operation to mention but a few. This measure thus eliminates the seemingly difficult task of having to analyse the individual computer skills of users by enabling the focus to only be on what users can perform on the BI systems regardless of the computer skills they have acquired. In addition, it enables the measurement of social effects that impact on IT usage at individual level (Easley, Devaraj and Crant, 2003; Lin and Huang, 2008; Hsu and Chiu, 2004 & Gallivan, Spliter and Koufaris, 2005), which is the surrogate unit of analysis in this study.

Embedded in the CSE construct is the interaction between the environment in which a computer application is used, and the behaviour of individual users towards a computer application (Compeau and Higgins, 1995; Compeau *et al*., 1999 & Thong, Hong and Tam, 2004). These authors suggest that the CSE for a user at any point in time is a reflection of the user behaviour and the overall environmental attitude of users about a technology. Thong *et al*. (2004) have further shown that positive usage of technology from the environment positively influences one's perceived ability to use a system. Thus users could be encouraged or discouraged to use a computer application based on whether the majority of the surrounding users apply or avoid this technology. This aspect of CSE also justifies applying the construct in this study, because it satisfies the highlighted need by DeSanctis and Poole (1994) & Dennis *et al.* (2001) that measuring IT usage with only TTF excludes the effects of the environment wherein the computer system and executed task exist.

2.3.3 Technology acceptance model

The technology acceptance model (TAM) was developed to explain and to predict technology usage as a self-reported measure (Doll, Hendrickson and Dong, 1998). It has its foundation in the theory of reasoned actions (TRA), which shows that beliefs influence attitudes, which in turn influence behaviour (Argawal and Karahana, 2000 & Venkatesh, 2000). TAM suggests that an individual's intention to use a technology is influenced by two beliefs, perceived ease of use (PEOU) and perceived usefulness (PU) (Venkatesh and Davis, 2000 & Venkatesh, 2000). Venkatesh and Davis (2000) define PU as the belief by a user that using a technology will improve the execution of his/her task. In addition, they define PEOU as a user belief that using a technology will require no additional effort other than the perceived minimum effort necessary to complete a task. Figure 3 shows the model, its constructs and their relationships. PEOU is shown to impact on the intention to use a technology and in addition, to impact on the usefulness of a computer system. PEOU has however reflected stronger effects as a determinant of perceived usefulness than as factor impacting on usage (Doll *et al*., 1998 & Venkatesh, Speier and Morris, 2002), suggesting that the model should be adjusted such that PEOU only determines perceived usefulness. These (PEOU and PU) are two widely tested belief constructs, which so far have given consistent results in assessing intentions towards using a technology (Cheng, 2011; Chau, 1996; Koufaris, 2002 & Lee, Kozar and Larsen's (2003). TAM as a model for IS adoption, however, has been mainly tested with students as participants, thus validation of the model in non-academic settings is lacking (Lee *et al.,* 2003).

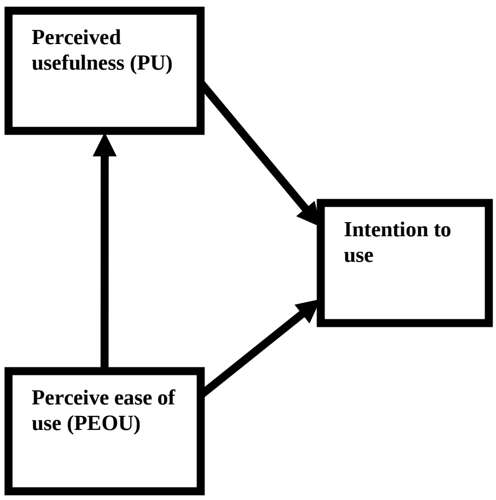


Figure 3: A model of TAM adapted from Venkatesh and Davis (2000)

The consistent manner in which TAM has performed in previous studies leads to its choice to measure user beliefs on the BI system at SA-Bank. A measure of beliefs towards using a BI system as enabled by TAM, a self-reported measure, is inevitable given the motive of the study to solicit individual user views. Moreover, the choice to use a technology is preceded by the beliefs that users have regarding the capability of the technology (Vessey and Galletta, 1991). Thus TAM appears to fit the objectives of the current study.

There are however limitations to applying only TAM for measuring IS usage. The first one is highlighted by Dennis and Reinicke (2004), who noted that TAM disregards the effect exerted by the environment wherein a technology is applied. CSE was however identified in this study as a measure which could enable the inclusion of the environmental effect. Thus, the application of CSE to extend the measurement capacity of TAM is justified. Wixom and Todd (2005) & Venkatesh (2000) also suggested that TAM applied as the only measure for IS adoption does not result in information that is useful for system design, because only two views, usefulness and ease of use, are delivered as an outcome of such measurement and not practicable information. In contrast to this view, Dennis and Reinicke (2004) suggested that TAM enables analysis of technology perceptions of a user in the light of the tasks that are to be performed, suggesting that it results in implementable outcome. Whether the view by these authors is correct or not, TAM still cannot result in system details or descriptive qualities of tasks that are executed with the system, because system and task qualities are not beliefs but possibly determinants of beliefs (Wixom and Todd, 2005). Thus, TTF is used as an extension to TAM in order to enable capture of both the task and system features that influence BI system usage.

2.4 Research Model and hypotheses

Figure 4 shows the research model. The intention to use a BI system at SA-Bank appears to be influenced by user capability characteristics and the combined effect of system and task features. The model joins constructs from the theoretical frameworks discussed above in performing this analysis as follows: TAM assesses user beliefs of the extent to which the BI system is perceived useful (PU) and easy to use (PEOU), and the intention to a BI system (IU); CSE measures the user capability to operate the BI system and TTF measures the fit between decision tasks and the BI system, and the system and task features.

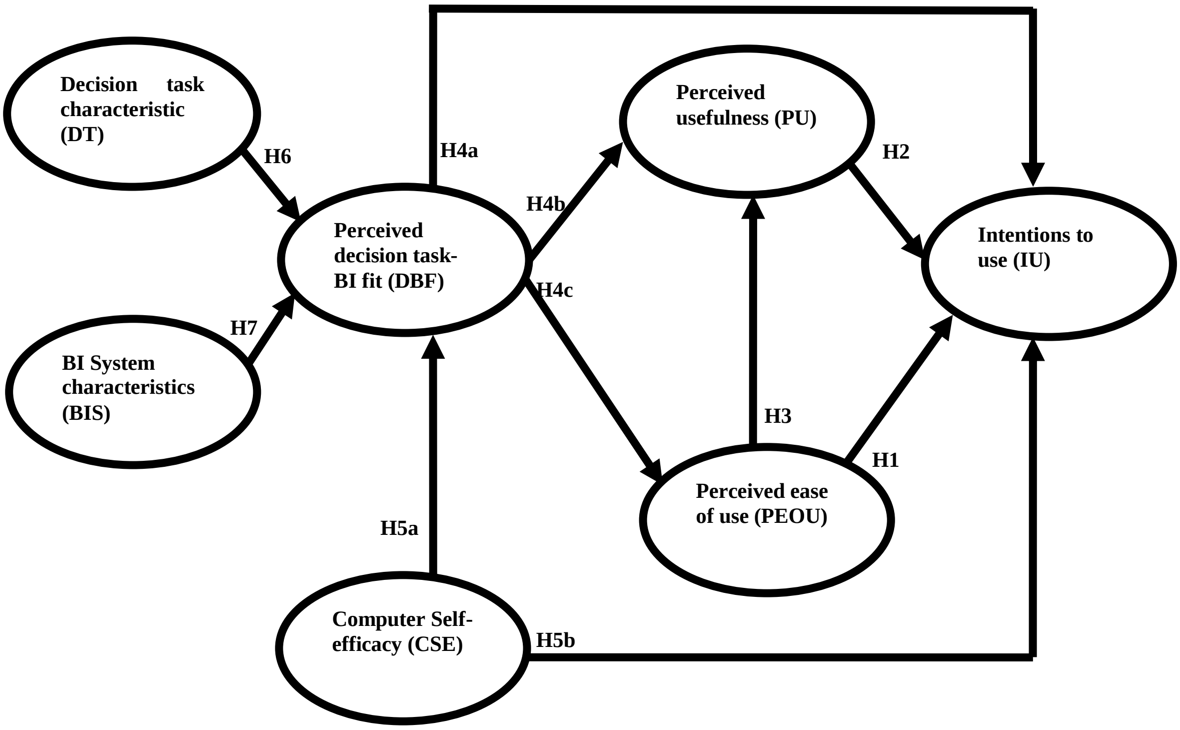


Figure 4: Research Model

2.4.1 User beliefs and BI system usage

TAM is applied to analyse the beliefs that users have of the BI system (an existing system) at SA-Bank. PEOU, one of the two belief-constructs comprised in TAM, is a user view of the effort necessary to execute a task (Argawal and Karahana, 2000). During decision task execution, a user applies his/her judgement with regards to the decision task at hand, and how much effort is needed to execute this task. Therefore, the effort to be expended will determine whether the user goes on to apply the technology aid when performing a decision task or not. To reiterate, decision makers use a BI system according to what Moon and Kim (2001) term intrinsic motivation, which means technology utilisation arises only from the belief that it is rewarding to apply a computer system. In this context, the reward for using a BI system is the perception by users that using it will help them perform their decision tasks with the minimum required effort. Thus, the perception that the BI system only requires an effort perceived to be necessary to complete a task will encourage usage, while the perception that the BI system requires more effort than could be expended to complete a decision task will discourage usage. The impact of PEOU on the intention to use a technology is supported in IS research (Koufaris, 2002 & Venkatesh and Davis, 2000). A study by Venkatesh (2000) which was done to determine technology usage over time also extends the view that PEOU has a significant direct effect on the intention to use a new technology, but with such an effect diminishing over elapsed time. Therefore, it is suggested that for a BI system, the PEOU of decision makers is positively related to the intentions to use a BI system.

H1: *The perceived ease of use of a BI system will positively affect the intention to use the BI system*.

Chau (1996) describes PU as the belief that executing a task through technology will lead to an expected output. Answers to two questions affect this perception according to PU discussions in the IS literature. The first question asked by a user is: *does the technology enhance the execution of a decision task* (Chau, 1996; Wixom and Todd, 2005; Moore and Benbasat, 1991 & Moon and Kim, 2001)? Another question implied in IS literature is: *is the output resulting from usage of a specific technology an expected output* (Chau, 1996; Dennis and Reinicke, 2004)? So, from these two questions, it becomes apparent that PU is a function of task execution as well as technology output. This relates to the needs of decision makers at SA-Bank. As a voluntary system, there are other systems or methods that can be used by decision makers to extract data and information for decision support. For instance, one call-centre unit could still follow the old custom of manually extracting data from a transaction processing system into spread-sheets towards decision support, should they perceive the BI system to be lacking in usefulness. Although this practice has since been substituted with BI system processing, users who are familiar with it, however, could still use it as an alternative to the BI system processing depending on their perception of the usefulness of the BI system. Therefore, a hypothesis is stated that these users would only choose to use the BI system should they perceive that it better enhances completion of decision tasks, in comparison with the old system. Otherwise, it is suggested that users will avoid applying the BI system should they perceive that it prolongs their completion of decision tasks.

H2: *The perceived usefulness of a BI system will positively affect the intention to use the BI system.*

The effect of PEOU in TAM literature is reflected to be significant and positive to both perceived usefulness and the intention to use a technology, indicating practical significance of PEOU as a predictor of IS usage. In this study, a proposal similar to the relationship suggested in TAM (between PEOU and PU) is stated as follows: the ease of using a BI system exerts a positive influence on the extent to which a BI system is perceived to be useful. The ease of using a BI system could lead to the perception that the BI system is useful, only if users perceive the system to require effort that is necessary to complete decision tasks. The lowest possible effort to execute a task means that time is spent in doing only what is necessary to complete a decision task. It further implies that the task is completed in the minimum possible time. To recapitulate, PU is also a belief about how technology enhances task performance, implying that the speed with which a task is completed is fundamentally important where perceived usefulness is concerned. Therefore, if the interaction with a BI system is regarded as effortless, a PEOU attribute, then the BI system could be perceived as efficient, a PU attribute, because effortless could also be interpreted to mean reduced time, hence enhanced task performance. Therefore, the perceived ease of using a BI system appears to positively relate to the perceived usefulness of the system. The influence of the perceived ease of use on the perceived usefulness of a technology is supported in several studies in IS (Chau and Hu, 2002; Argawal and Karahanna, 2000; Venkatesh *et al.,* 2002 & Venkatesh and Davis, 2000), leading to hypothesis H3 about a BI system.

H3: *The perceived ease of use of a BI system will have a positive effect on the perceived usefulness of the system.*

2.4.2 Perceived task-BI system fit and intention to use

TTF studies show that the fit between a technology and a decision task leads to the utilisation of a technology (D'Ambra and Rice, 2001 & Dennis *et al*., 2001). The perceived extent to which a technology matches the task that users perform with it determines whether utilisation will occur or not. The same is suggested for the BI system at SA-Bank, namely that how users perceive it to be matching the needs of decision tasks as processed by users, will affect the extent to which the technology is used. It implies that as users attempt decision tasks with the BI system and find that it has all functions that are needed to complete these tasks, they then will be inclined to use the system. The opposite could also be true, namely that if users find it difficult to perform tasks with the BI system, because it lacks some or all of the functions needed to solve decision problems, then users will be disinclined to use it. Although Zigurs and Buckland (1998) suggest that the only usage that leads to performance enhancement is good usage, this is only noted but not tested in this study, viz. that more usage could be problematic if it results in negative consequences. Therefore, the idea of more usage in this study is one resulting in the organisation benefiting from employing the services of a BI system. It is thus hypothesised that the perceived fit between a BI system and decision tasks (DBF) constituting a user's task profile, will affect the intention to use a BI system.

H4a: *The perceived decision task-BI fit will positively impact on the intention to use the BI system.*

As mentioned above, a technology is perceived useful if it helps users perform their tasks efficiently, and when the resulting output aligns with user expectations of the details that are necessary to resolve decision tasks. With positive perceptions of the usefulness of technology, users could conclude that using it will result in their performance of decision tasks being enhanced. This view is also shared by Lee *et al*. (2007) that, aligning a technology to the decision task needs is equivalent to facilitating task performance. This therefore leads to the suggestion that matching BI system functions to decision task needs could also have a direct impact on the perceived usefulness of this technology. A contrasting view to this could be stated as follows: a misalignment of decision task and the BI system qualities could imply that the BI system lacks in the functions that are needed to complete decision problems (or decision tasks). It could be that the BI system has functions which match some of the decision task needs, or functions that are totally misaligned to the needs of decision tasks. Whether it meets some needs or none of the decision task needs, it is regarded as a misfit to the decision task needs, thus negatively impacting on perceived usefulness. It is thus proposed that for the BI system being studied, the perceived fit between the system and the decision tasks positively relates to the perceived usefulness of the BI system.

H4b: *The perceived decision task-BI fit is positively related to the perceived usefulness of the BI system.*

The perceived fit between a technology and a task is found to have a positive influence on usage (Goodhue, 1998). In this discussion a contextualised view (to the BI system at SA-Bank) is suggested, that the perceived fit between a BI system and a decision task will have a positive influence on a user's belief that the BI system is easy-to-use. This perception, of course, subsequently leads to the intention to use or not to use the BI system. A BI system is a technological aid facilitating execution of decision tasks (Lawton, 2006). This suggests that the BI system should be equipped with every function that is necessary to complete decision tasks, because only then would the system assist users meet their goals. Lee *et al.* (2007) extended support of this view in their statement that, when a technology has all the functions a user could possibly need to execute a task, and these functions indeed support the execution of the task, then the task is performed easily and effectively. Further, Mathieson and Keil (1998) stated that the ease of using a technology is beyond the layout design of the user interface of a computer technology. They suggested that the ease of computer usage is not only dependent on how easy it is to perform commands from the computer interface or how user-friendly the computer interface is, but also about how effective are the computer functions when a user performs tasks. It is thus implied that the effort to complete a task is minimised when the computer functions deliver information exactly according to the requirement of decision tasks, suggesting that task–technology fit influences the ease of using a system. Support was found in Mathieson and Keil (1998), that the perceived fit between a task and technology is positively related to the ease of using a computer application. Thus the hypothesis that the perceived fit between a BI system and a decision task will positively influence the ease of using a BI system.

H4c: The *perceived decision task-BI fit is positively related to the perceived ease-of-use of the BI system.*

2.4.3 The effects of computer self-efficacy on usage

Venkantesh (2000) views the ability to control a computer application as one factor that could inhibit or enable execution of tasks through the computer software. The perception formed by a user of his/her computer-control ability is known as computer self-efficacy (Compeau and Higgins, 1995). Computer self-efficacy has been shown to influence PEOU and PU, constructs of TAM (Lewis, Agarwal and Sambamurthy, 2003), to directly predict task performance (Yi and Davis, 2003), and to influence the perceived fit between decision tasks and technology (Lin and Huang, 2008).

In this study, it is suggested that for a BI system, one's computer self-efficacy influences his/her perception of fit between decision task and the BI system. A fit implies that a user has conceived the needs of the task to be executed, and has identified the functions to be executed (Goodhue, 1998). A user could require a certain level of ability on how to operate these functions in order to accurately assess whether a fit exists between a task and a technology. Furthermore, even if a user knows that the functions that could enable him/her to perform a task are available, this information will not help with task completion if the user perceives that s/he is not capable of executing the identified functions. Thus although the match between a task and technology could be perceived to exist by a user, the evidence of a fit would only be available after the execution of the task is completed. This implies that when a user fails to complete task execution because he or she was unable to operate a computer function, then there is a greater likelihood that the user will perceive the technology to not match the task needs, because there is no evidence of system meeting task needs. Therefore, whether a fit between task and technology exists or not also depends on one's perceived computer self-efficacy. This could also be true for a BI system that, users with a positive perception of ability to operate BI functions will view the BI system as matching the task needs, while users with a negative perception of ability to operate BI functions will view the BI system as misaligned to task needs. Thus it is proposed that computer self-efficacy positively impacts on the fit between decision tasks and the BI system.

H5a: *Computer self-efficacy positively relates to the perceived decision task-BI fit.*

CSE is found to positively impact on both actual usage and self-reported usage of a technology (Easley *et al.,* 2003 & Compeau and Higgins, 1995), but also suggested by Strong, Dishaw and Bandy (2006) is that CSE affects technology usage via a combined effect with technology qualities. In the BI environment at SA-Bank, it is suggested that usage depends on how well users perceive that they have the ability to execute decision tasks with a BI system. This perceived ability can also be explained by the level of confidence that a user has towards executing a task (Thong *et al.,* 2004 & Lee *et al.,* 2007).

If a user perceives that s/he is able to perform a task with a technology, without challenges of identifying and executing relevant functions, then the user will be inclined to use the technology given an opportunity. Again if a user doubts his/her ability to use a technology, there is a greater likelihood that the user will avoid using the technology under any circumstances. Computer self-efficacy also encapsulates the effects of the environment wherein a user operates (Gallivan *et al.*, 2005 & Compeau and Higgins, 1995). This implies that when positive usage dominates the environment wherein a technology is adopted, then there is a chance that the CSE of a user will be positively influenced, resulting in more usage. On the contrary, when there is generally a negative attitude towards a technology by the intended user community, then a user could form beliefs that he/she is less capable to use the technology, resulting in the rejection of the technology. A hypothesis is thus stated that at SA-Bank, the computer self-efficacy of a user will positively affect his/her intention to use the BI system.

H5b: *Computer self-efficacy positively relates to the intentions to use the BI system.*

2.4.4 Decision task and BI system characteristics towards use

Zigurs and Buckland (1998) define a decision task as a task that has several potential outcomes. A BI system as a decision support aid enables a user to reach these outcomes, upon which this user applies his/her knowledge to pick an outcome that resolves a problem. Depending on the nature of the decision task or the time and effort required to interact with the BI system towards these outcomes, the system could have varied levels of usefulness towards solving a decision task.

Zigurs and Buckland (1998) also suggested the complexity of a task as one attribute that could increase both the information load processed by a user to complete a task, and the length of processing time taken by a user to complete a task. The complexity of a task could thus affect the manner in which a user interacts with a BI system with regards to time and effort.

Goodhue and Thompson (1995) found support for two other task attributes which affect the nature in which a user interacts with technology, task ambiguity and interdependence. The authors define task ambiguity as the extent to which a user believes that what s/he understands as a requirement of the task is indeed a requirement of the task. If a decision task is conceived to be unclear or if its requirements are not clearly specified, then identifying relevant functions from the BI system could be difficult for the user. This could imply prolonged interaction of a decision maker with the BI system. The opposite could also be true, namely that clearly defined decision tasks lead to completion of a decision task in just the time necessary to complete it, because a user is not left to guess the likely meaning of a requirement in order to pick a relevant function from the BI system. Task interdependence is discussed by Goodhue and Thompson (1995) as the degree to which users communicate while attempting execution of decision tasks. A decision task could incite communication from different users, an action which can facilitate performance of the task, because different users could possess different views of performing the same decision task. Therefore, the need to share information between co-workers (task-interdependence) could also imply that the time and effort that is spent executing decision tasks with a BI system are reduced.

When tasks are executed in just the time and effort necessary for their completion, because they are clearly stated, easy or encourage solicitation of co-worker input, then users could perceive the BI system as meeting decision task need. Conversely, when tasks are executed with effort and time that are in excess of the effort and time necessary for their completion, because they are unclearly stated, complex or reliant only on independent user effort, then users could perceive the BI system as misaligned to decision task need. Thus it is hypothesised that, for a BI system, decision task characteristics (DT) positively impact on the fit between task and technology.
H6: *Decision task characteristics positively impact on the perceived decision task-BI fit.*

Four attributes of a computer technology are considered in this discussion, namely: the extent to which users find the BI system available to service their information needs; the extent to which the BI system meets the changing decision task need; the ease with which the BI systems makes information available to users and the rate at which the BI system processes user requests.

Firstly, a BI system that is seldom available when users need it for executing decision tasks delays the process of decision making and prolongs the time necessary to complete tasks. Conversely, a system that is available every time it is needed enables execution of decision tasks as and when business activity calls decision users to do so.

Secondly, the extent to which a BI system matches the needs of decision tasks as they change, could also affect the effort and time necessary complete decision tasks. New or changed business needs could imply that users are now required to process more information than before, or engage in more interaction with the BI system than before, therefore, both these are likely to increase the effort and the time to complete tasks. An IS, however, can be designed such that users are not affected by the changing business needs in terms of their interaction with the system, a design that could positively impact the user perception of fit between task and technology.

Thirdly, the user view of the ease with which information can be accessed from the system is another attribute of a BI system which is of interest in this study. Should a system require that users engage in lengthy interaction with it before they get the required outcome, then users could believe that the system delays task performance and requires more time than necessary to complete tasks.

Lastly, the rate at which a computer system processes the output that is requested by users impacts on the time necessary for task completion. Lengthy processing times of user requests imply delayed execution of tasks, and could lead into a belief that the BI system is not aligned to the requirements of decision tasks.

These BI system features could lead to a belief that the BI system does not match the decision task profiles of individual users, should they negatively affect the time perceived necessary to complete decision tasks. On the other hand, should the BI system require only time and effort necessary to complete tasks, users could perceive that it meets decision task needs.
H7: *BI system characteristics positively impact on the perceived decision task-BI fit.*

2.5 Chapter summary

This chapter discussed the usage types of a BI system, leading to the identification of the kind of BI system usage focused upon in this study. Four types of BI system usage, tactical, diagnostic, evaluative and strategic, were identified and these were also distinguished from one another. The BI system at SA-Bank employed two types of usage, diagnostic and strategic, but the study focused on diagnostic usage because the number of users employing this usage type exceeded the required minimum for statistical analysis. The chapter also discusses three theoretical frameworks, TTF, TAM and CSE from which constructs to measure the properties of a BI system usage are derived. These constructs are adapted in the study for their consistency in measuring IT usage. Finally, covered in the chapter is the research model which is a basis for hypothesis testing.

CHAPTER 3: RESEARCH METHODS

3.1 Overview

This chapter focuses on the description of methods that were used to gather and analyse data for purposes of this study. The discussion begins with an outline of the paradigm in which the study is based. This lays the ground for subsequent discussions in this chapter as different paradigms have different techniques for research (Orlikowski and Baroudi, 1991). The chapter further covers the design layout of the method used to gather data, looking specifically at the operationalisation of the constructs discussed in Chapter Two, and the control variables focused upon in the study. Furthermore, the environment wherein the sample was drawn together with the sampling technique deployed, is discussed. Discussion of the validation of the instrument used to gather data is also covered, followed by a discussion of the approach employed when applying for an ethical clearance certificate, a prerequisite for data collection. Finally, before concluding the chapter, methods performed to clean data, assess construct validity and reliability and test hypothesis are outlined.

3.2 Research approach

The research approach followed in conducting this study draws from a positivist paradigm. This paradigm was chosen since the aim of this study was to determine factors which impact on BI system usage and specifically assessing the extent to which identified factors impact on the usage of a BI system. In line with the discussion of Kaplan and Duchon (1988), a positivist paradigm presented a wide choice of statistical techniques, which satisfied this need. Moreover, in comparison to using a qualitative paradigm, associated with methods that seek to explain in depth how a specific context influences an IS phenomenon, thereby binding research outcomes to context (Lee and Hubona, 2009), the finding of this study can be applied in contexts beyond the SA-Bank boundaries.

3.3 The BI environment

There were over 2000 users of the BI application at SA-Bank at the time of study, and approximately 2500 users when including partners of SA-Bank. Several examples of how BI usage takes place within SA-Bank were discussed in Chapter One and Two, but essential to note is that the BI system within SA-Bank spanned all business units, that is, it was applied within other business units besides the credit and call-centre unit as stated in the examples.

The BI system was non-mandatory to the BI user community, which is normally a condition for decision support systems (Nagesh, 2004 & Lönnqvist and Pirttimäki, 2006). Therefore, usage at this firm arose from the user view of whether the decision task one is about to execute required data processing from the BI or not.

3.4 Unit of analysis

The unit of analysis was the BI system, however, individual user views were used as surrogate units of analysis. Such an approach was appropriate given that the BI system had not reached organisation wide usage (Leidener and Elam, 1995), that is, users in some areas of the organisation were not relying on the system for task completion. Consistent with the statement by the same authors, namely that low level analysis can be transformed into organisational level conclusions, analysis was performed at individual level and not organisational as would have been ideal. The implications, however, were interpreted to apply at organisational level.

3.5 Research Design

A survey methodology was chosen for the purpose of this study for reasons subsequently discussed. This section is made up of three parts as follows:

- A background of the survey methodology in light of the purpose of the study.
- A discussion of the constituents of the survey questionnaire.
- Control variables.

3.4.1 A survey methodology and the purpose of this study

The aim of the study encapsulated the intention to extend validation of BI system design factors beyond the context of SA-Bank. The challenge therefore was to ensure that all aspects from the BI system user community at SA Bank relevant to this investigation are captured, because BI system usage at SA-Bank spanned various geographical locations in South Africa. Applying a survey technique promised attainment of this goal, because it offered the flexibility of applying communication techniques that enabled a reach to participants that is unlimited by geographical space, such as Post Office facilitated communication, internet and email (King and He, 2005). In this study email was therefore used to administer the survey instrument for the reason of enabling wide coverage. More importantly, email was adopted because of the limited time allocated for this study (Yu, 2003 & Sivo, Saunders, Chang and Jiang, 2006).

3.4.2 Scales and measurement items

The survey was made up of two sections, A and B. Section A had items measuring the theoretical constructs of the study, while Section B comprised the questions that were used to get demographic information from respondents. This order of sections was used to avoid alienating respondents from participating in the study due to asking personal questions before the main survey questions were presented to them (Bailey, 1994).

A literature review was conducted to identify measurement items from past studies which were used in this study. Based on this exercise, validated measurement items were identified for all the constructs (or scales). A few of the measurement items were taken as they were used in past studies, but the majority had to be adapted to suit the purposes of this study. Additionally, as recommended by Churchill (1979), scales should be made up of multiple measurement items in order to reduce measurement error. Therefore, each of the scales of this study comprised four items. Each item that measured a concept of the study beared a 7-point Likert-type design ranging from 1 “strongly disagree” to 7 “strongly agree”, because such a format is known to improve the reliability and validity of scales when variation in answers is anticipated to be wide, as was the case in this study (Hair, Black, Babin, Anderson and Tatham, 2010).

An example of the scale 'intentions to use' (IU) is used to illustrate how the majority of measurement items were adapted from various studies. Items for construct IU were adapted from Cheng (2011) & Wixom and Todd (2005). These items were taken as they were in the above mentioned studies, with only a few terms changed to make them relevant to the context of this study. For example, 'I intend to use the system at every opportunity' from the study by Wixom and Todd (2005), was changed to 'I intend to use the BI system at every opportunity' (see Appendix A for a complete list of items).

3.4.3 Control variables

The study comprises five control variables: job-role, age, gender, education level and user BI experience. Job-role, represented by item 2 of section B of the survey instrument, was created to solicit the level of employment of respondents. To recapitulate, the BI system usage that is of focus in this study is diagnostic usage, but given that there was another type of usage, strategic usage, observed within the SA-Bank context, diagnostic usage had to be isolated from strategic usage. Thus job-role served this purpose. With senior managers (executives included) only using aggregated data, that is, data spanning business units and time, and lower management levels using data that were bound by their respective areas of responsibility, job role appeared to be a valid proxy for differentiating between usage types. In addition, age, gender, education-level and user BI experience were also controlled in order to assess their influence on the findings of this study (Gallivan, *et al.*, 2005, Srite and Karahanna, 2006 & Burton-Jones and Hubona, 2006).

3.5 Sampling method

From the discussion of the study context, 2000 users were identified as participants. With partial list squares (PLS) identified as a primary data analysis technique for reasons discussed in Section 3.9 below, a minimum of 150 responses was necessary (Hair *et al.*, 2010). This sample size is also a threshold for a study that is comprised of seven variables according to these authors, a condition for this study. PLS literature, however, suggests that researchers applying this technique should use the following as a rule of thumb for determining the minimum sample size of a study: count the number of paths pointing to the different constructs in a research model, pick the highest count and multiply by 10. This exercise resulted in a minimum sample size of 40 responses being identified as necessary for the statistical analysis of this study. Multiple regression, however, was also used as a validation technique thus the sample requirement also had to meet the need for this technique over and above that for PLS. A minimum sample size of 150 was thus an automatic choice for this study, because it is a denominator of minimum data requirement for the two techniques to be applied in the data analysis of the study (Pallant, 2007 & Hair *et al.*, 2010). Taking into account also that for IS studies, 22% is recorded as an average response rate (Sivo *et al*., 2006 & Yu, 2003), the study was therefore administered to 682 (150 x 22%).

3.6 Pre-study analyses

The survey instrument was pre-tested and pilot tested to ensure content validity (Moon and Kim, 2001; Moore and Benbasat, 1991; Chau and Hu, 2002 & Straub, 1989). A pre-test was done to ensure that each individual question in the survey instrument only identified with the construct it theoretically related to and to guarantee that every set of items making up a scale, collectively represented all aspects of the corresponding concept (Chau and Hu, 2002). A pilot test was performed to examine the respondents' likely perceptions of the wording and layout design of the content of the survey instrument (Leidener and Elam, 1995).

3.6.1 Pre-test

Ten industry experts with more than 2 years experience in the BI environment and 4 experienced academics participated in a pre-test exercise of the study.

3.6.2 Pilot test

A pilot test was run on a sub-sample that was representative of the primary sample of the study. This test was conducted in the same manner as the approach which was used to administer the main study (covered in Section 3.8).

3.7 Ethical clearance

Using Chau and Hu (2002) as guide because of the similarity in settings between the one in their study and SA-Bank, before sending out the questionnaire, a request letter (see Appendix B) to solicit participation was sent to managers of the various SA-Bank units which use the BI system. This letter explained the purpose of the study, ensured confidentiality and anonymity and explained the voluntary nature of the study, which are mandatory requirements for ethical research conduct (Human Science Research Council, 2011). Consenting managers responded with a list of potential participants. These unit members were subsequently sent the same letter soliciting their participation. A database was created with names and corresponding e-mail contacts of individuals who responded positively. This database is the same list that formed the sample frame of this study. An ethical clearance with protocol number, CINFO/1010, was obtained from the University's ethics committee and the letter declaring approval of the ethical clearance application appears as Appendix C of this study.

3.8 Study administration

Freeonlinesurveys, an internet application for conducting surveys was employed as a survey presentation interface to participants, and also as a data capturing instrument. The questionnaire was e-mailed to the various subjects with a cover letter (see Appendix D) which re-assured confidentiality, anonymity and voluntariness, and a link (see Appendix A) referring participants to the Freeonlinesurveys interface which was configured to present the study.

3.9 Preliminary data analysis

The following analysis was performed with IBM's SPSS trial version 18.

3.9.1 Data Screening

The data was screened for missing data entries and systematic response error patterns. In addition, measurement items were assessed for outliers, linearity, homoscedasticity and normality, which are assumptions for regression analysis. This exercise was performed as a further data cleaning exercise in research (Hair *et al.*, 2010).

3.9.2 Non-response bias test

One way to determine the existence of non-response bias is to check if there is a pattern in responses between early and late respondents (Sivo *et al.*, 2006). This same approach was chosen for detecting non-response bias in this study, because it was convenient for one to rely on results that were already available rather than using for instance, weighting adjustment, which involves making telephone calls to people who did not want to respond in the first place. A multi-variate analysis of variance (MANOVA) was used for this exercise (Doll *et* al., 1998).

3.9.3 Factor analysis

Principal component analysis (PCA) with non-orthogonal rotation was used. Prior to this analysis, however, the Bartlett test of sphericity (significance shown by a magnitude more than 0.5) was performed to determine whether the measurement items of the study exhibited sufficient correlations to warrant factor analysis to proceed. The latent root criterion was therefore analysed to determine valid factors, with eigenvalues of greater than 1.0 used as cut-off for factor selection. This method was supplemented by a scree test curve analysis to guarantee a correct selection of factors (Pallant, 2007). Convergent and discriminant analyses were assessed by the test for unidimensionality (Hair *et al.*, 2010). Finally, Cronbach's alpha was used to determine internal consistency (or reliability), and only magnitudes in excess of 0.7 were considered significant (Gefen *et al.*, 2000).

3.9.4 Multicollinearity

To increase the chances of detecting the existence of collinear factors, tolerance and variance inflation factor (VIF) values for independent variables were assessed (Grewal, Cote, and Baumgartner, 2004) together with bi-variate correlation values (Zhang and Watts, 2008). Multicollinearity was considered a significant problem when the tolerance value for any variable was 0.1 or above, which corresponds to a VIF of 10 or higher, coupled with a correlation value of 0.7 or higher between any pair of variables (Hair *et al.*, 2010).

3.9.5 Common method bias

Common method bias, a term in research describing the distortion of findings due to asking participants to respond to questions on both the dependent and independent variables (Podsakoff, MacKenzie, Jeong-Yeon and Podsakoff, 2003), was assessed with Harman's single factor analysis and the latent common factor approach. With Harman's single factor approach, the data gathering method of this study was regarded to be free of common method bias when one factor (the first factor in PCA) accounted for insignificant (less than 50%) of covariance among research model measures (Podsakoff *et al*., 2003). The latent common factor approach was applied to confirm the existence of trivial method bias. With this approach, bias was considered problematic when the variance accounted for by a latent factor, made up by all measurement items of this study, was less than 25 % (Zhang and Watts, 2008).

3.10 PLS data Analysis

SmartPLS version 2.0 was used for primary data analysis. PLS was chosen because it is designed to maximise variance explained by predicting variables unlike its counterpart linear structural relations (LISREL), which seeks to reproduce the observed covariance of constructs (Hair *et al.*, 2010). The intention of this study was to assess the extent to which factors impact on the BI system usage, thus use of PLS satisfied this need of the study. Also, the exemption of PLS from most of the assumptions of statistical analysis techniques has made it a preferred choice for this study over the LISREL technique.

3.10.1 Construct validity and reliability

Convergent and discriminant validity were performed to confirm the findings of factor analysis above. In addition, reliability checks were performed as a way of showing both convergent validity and internal consistency of the scales (Strong *et al.*, 2006; Pitt, Watson, and Kavan, 1995). Convergent validity was evidenced when the loadings of related measurement items were significant, above 0.7, on the construct they are theoretically assigned to measure, and the construct reliability was likewise significant above 0.7 (Strong *et al.*, 2006). The test of significance was based on the t-values obtained from the bootstrapping algorithm with a critical threshold of ±1.96 (Gefen, 2002).

One method of showing discriminant validity is by observing the average variance extracted (AVE) of individual constructs (Igbaria, Guimaraes and Davis, 1995 & Nelson, Todd and Wixom, 2005). With this approach, discriminant validity would have been shown when the AVE for any construct is larger than that of correlated constructs in the research model (Gefen and Straub, 2005; Compeau *et al.*, 1999 & Nelson *et al.*, 2005). For the purposes of this study, however, a confirmatory method which entails analysis of latent variable crossloadings was applied (Lewis *et al*., 2003). A construct reflected discriminant validity when related items collectively indicated higher values for the construct they are theoretically assigned to measure when compared with items from other constructs of the study. Internal consistency, or reliability assessment, was statistically significant when the composite reliability coefficients were 0.8 and above (Gefen *et al.*, 2000).

3.10.2 Hypothesis testing

The strength of the model for predicting dependent variables was assessed with analysis of the coefficient of determination (R^2). A high R^2 was regarded as a sign for good model strength (Gefen, 2002 & Hair, *et al.*, 2010). Path coefficients were used to determine the strength between dependence relationships (that is, relationships between independent and dependent variables), while corresponding t-values were used as indicators for statistical significance (Igbaria *et al.*, 1995). A strong relationship was reflected by a combination of high coefficient magnitude and the extent to which a p-value is above the statistical significance level. Statistical significance was shown when t-values (of paths) reflected values in excess of ± 1.96 or alpha levels of 0.05. (Gefen *et al.*, 2000).

3.10.3 Control variable effects

An analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA) were used where necessary to test for any difference within the groups of the control variables of this study. Significance testing of both analysis techniques followed the guideline given by Hair, *et al.* (2010) & Pallant (2007).

3.11 Regression Analysis

Multiple regression analysis was performed as a confirmatory approach for the PLS hypothesis test outcomes, especially to assess whether individual predictors impacted consistently on the criterion when considered in isolation of other predictors (Gefen, 2002). From this approach, a standard multiple regression analysis was performed in this study. Conditions required for multiple regression analysis, namely, outliers, linearity, homoscedasticity and normality, were performed as recommended in research (Pallant, 2007). The multiple regression statistics of interest were the coefficient of determination (R^2), Adjusted R^2, beta-coefficients and the ANOVA F ratio. Interpretation of the statistics followed the same standards explained in the discussion for hypothesis testing above except for the Adjusted R^2 and ANOVA F ratio which was interpreted according to IS established multiple regression standards.

3.12 Limitations

Limitations were inherent in the paradigm in which the study is based and data analysis techniques which are used in this study. The method of incorporating social context to the investigation of a study with only computer self-efficacy assessment, entails fixing other environmental variables which could be exerting impact on the examined phenomenon (Orlikowski and Baroudi, 1991). A distortion of findings therefore could arise when the effects of these (unidentified) variables are non-trivial to the phenomenon of this study. Finally, the limitations inherent in the statistical techniques used in this study (PLS and multiple regression) such as the lack of agreement on the minimum required sample to perform PLS (Jarvenpaa, Shaw and Staples, 2004), and the dependence of multiple regression on data linearity, normality and homoscedasticity (Hair *et al.*, 2010) set the upper bound for the accuracy of the results of this study.

3.13 Conclusion

This chapter discussed the background of the procedure followed in gathering and analysing data, and the paradigm in which this methodology is based. The next chapter outlines the results of applying all the techniques discussed in this chapter.

CHAPTER 4: DATA ANALYSIS

4.1 Overview

This chapter presents analysis of the results of the study. The chapter begins with the stating of the findings of pre-study instrument validation before the exercises of data cleaning and normality checks are discussed. The make-up of responses in light of the control groups used in this study is also stated. Thereafter, the outcomes of factor analysis and confirmatory factor analysis are explained in the listed order. Furthermore, the outcome of the analysis of non-bias tests (both response and method biases) are presented. Lastly, the results of hypothesis testing are discussed followed by the stating of the conclusion of the chapter.

4.2 Preliminary instrument analysis

Pretesting the instrument highlighted that measurement items of two constructs, intentions to use (IU) and computer self-efficacy (CSE), were overlapping, which necessitated rewording of the items. The outcome also highlighted issues relating to the layout of the questionnaire such as the order of measurement items making up the questionnaire. All the suggested changes were subsequently included in the design layout of the study.

A pilot test was run after the necessary modifications mentioned above were made. Of the 33 participants who were selected to participate in the pilot study only 18 responded with answers to all the questionnaire items, thereby yielding a 55% response rate. The results of the pilot test highlighted a need for further modification of the instrument content, because of the concern raised by some respondents that measurement items were being repeated in the questionnaire. This was resolved by rewording some of the items and grouping related measurement items together. An exploratory factor analysis was then run on the data resulting from the pilot study which reflected that a four factor solution was represented by the data. This result reflected a solution whereby TTF and PU loaded highly on one factor, an outcome which Dishaw and Strong (1999) suggest is likely to happen when TTF and TAM are joined to study an IS phenomenon. Therefore, a decision was made to proceed with the administration of the study to the, 682, identified potential participants.

A questionnaire, built with the Freeonlinesurveys online application, was randomly sent to individual participants by email. Due to time limitations, the length of the period of the study was set to three weeks. After this period a spreadsheet was downloaded from the online application, which reflected that 193 responses were received. Of the 193 who responded, 13 were at senior management level. These 13 responses were therefore excluded from further use in statistical analysis (see details in Chapter Two), thus leaving 180 analysable cases.

4.3 Data cleaning

All the mentioned tests in this section were performed with SPSS (version 18).

4.3.1 Missing Data Analysis

The outcome of the analysis of missing data reflected that all research variables have less than 5% missing data with no observable systematic patterns on the values that are missing (see Appendix E for table and pattern analysis outcome). Little's missing completely at random (MCAR) test was insignificant (sig. = .239), which indicated that the occurrence of missing data was completely random (Hair *et al.*, 2010). Due to the low percentage of missing data of variables, coupled with the randomness of missing data, all the missing entries were replaced by mean scores of variables (Hair *et al.*, 2010).

4.3.2 Outliers

The variables were first scanned for outliers with boxplots produced for each measurement item. The results of this analysis reflected that one case was an outlier in 10 of the 28 variables, and thus was subsequently deleted from the data set. Bivariate tests with scatterplots of measurement items grouped by scale, did not reflect any outlier. A multivariate inspection of outliers of all items with the Mahalanobis D^2 measure further highlighted 5 cases with magnitudes beyond the critical value of 24.32 applying a guideline by Pallant (2007). The five cases were also removed from further analysis. Finally, descriptive statistics were run for each of the measurement items and the table of means reflected that extreme values were not posing any serious effects, since the mean and the 5% trimmed-mean scores of all measurement items only differed by small margins. The similarity of the above compared means was also an indication that variable normality would be less impacted by further modification relating to outliers (Hair *et al.*, 2010).

4.4 Testing for assumptions

4.4.1 Linearity

Scatterplots were run for items of each construct to assess inter-item linearity between theoretically related measurement items of this study. Analysis of the outcome did not reflect any deviation from linearity except for item DT3 which appeared to have a non-linear relationship with the rest of the items measuring decision task characteristics. This item was then deleted from further analysis (Gefen *et al*., 2000). A sample of one of the bivariate scatterplots produced in this analysis to inspect linearity is attached as Appendix F of the study. The rest of the scatterplots reflected a similar trend to that depicted in the referred appendix, suggesting that the required state of linearity was met by the items retained for further statistical exploration.

4.4.2 Normality

Normality was assessed with normal probability plots, histograms and statistical tests. Normal probability plots indicated no serious violation of normality of the measurement items. Histograms with normal curve on the other hand, showed deviation of measurement items from normality. This deviation was also noted from analysis of the statistical values for kurtosis and skewness associated with the items. This analysis reflected that skewness values for all but two measurement items were above the critical value of ± 1.96 recommended by Hair *et al*. (2010). Further removal of cases which appeared as outliers from measurement items of concern did not result in any improvement on the magnitudes of kurtosis and skewness. Thus these cases were restored in the data set. Appendix G reflects a normal probability plot and a histogram of a decision task characteristics item, DT2, which reflected skewness and kurtosis values of -2.10 and -1.85 respectively. All other items reflected a similar trend of normality with the exception of PEOU1, BIS2 and CSE3, which had both skewness and kurtosis values extremely out of bounds. These items were removed from the measurement item set due for further analysis.

Two issues highlighted by Hair *et al*. (2010) on normality informed the decision that the observed violation of normality of the remaining measurement items would not distort the findings of multivariate analysis. One, the effective sample of the study was way above 50 (at

174), the implication is that the impact of non-normality would be minimal. Two, with the sample size of the study considered medium, and the modest violation of normality which was also mainly due to skewness, the data did not pose threats of outcome distortion.

4.4.3 Homoscedasticity

The scatterplots produced in the linearity sub-section above were further inspected for the presence of heteroscedasticity. Bivariate scatterplots of measurement items for each scale plotted against one another resulted in points shaping up to resemble an imaginary rod-like (or cigar) shape, suggesting homoscedasticity (Leidener and Elam, 1995). This observation was true between items grouped per scale for all constructs except for plots of items constituting the computer self-efficacy (CSE) scale. Therefore, CSE items reflected heteroscedasticity with points that were randomly scattered on the plot (Hair *et al*, 2010). Appendix F in addition to delineating linearity also reflected what was considered as a homoscedastic relationship in this study according to the same authors. The modest violation of homoscedasticity as reflected by CSE items was expected since the non-normality of these items was due to skewness (Hair *et al*., 2010). Thus all the remaining measurement items were retained for further analysis.

4.4.4 Correlation analysis

A correlation table was computed for all measurement items, and comparisons between related items indicated statistically significant values of the Pearson product moment (r) (Pallant, 2007). The corresponding r values were also greater than the threshold of 0.3 as suggested by the same author. One perceived usefulness item, PU1, however correlated strongly ($r > 0.7$, sig. = 0.000) with items of perceived decision task – BI system fit, DBF2 and DBF4, implying that PU1 could be measuring the perceived decision task – BI system fit concept instead of perceived usefulness (Gefen, 2002). Therefore, it was deleted from the measurement item set intended for multivariate analysis. A factor analysis was then performed for each construct to determine the variance explained by each item. This value was above the threshold of 60% for all items, therefore all items remaining thus far were retained for the next step of analysis.

4.4.5 Multicollinearity

After removal of PU1 as discussed above, all non-related measurement items (that is, items from different theoretical constructs) showed low to medium strength ($r < 7$, sig. = 0.000) correlations, an indication that multicollinearity was insignificant in this study.

4.5 Respondent composition analysis

Table 1 lists the make-up of the responses in terms of the control groups that were focused upon in this study. In terms of the three categories of seniority (or job levels) no noticeable difference was observed towards the intention to use a BI system at SA-Bank. Vandenbosch and Huff (1997) have, however, shown that usage of a decision support system differs based on job characteristics. Nonetheless, the similarity in usage across the seniority groups of this study could have been caused by the extent to which the decision task profiles of users

Table 1: Response group-breakdown

Group	Category	Percentage
Seniority	Junior managers	30.9%
	Middle managers	32.6%
	Non-managers	36.6%
Age	20 to 30	25%
	31 to 40	31.7%
	41 to 50	27.2%
	51 to 60	12.2%
Experience	1 to 2	21.2%
	2.1 to 4	32.8%
	4.1+	38.7%
Gender	Males	47.6%
	Female	52.4%
Education	Completed school	35.6%
	Completed a skills course	29.3%
	Bachelor degree	13.8%
	Master's degree	2.1%

across these groups were similar. In other words, although the seniority groups differed in terms job description, they were however similar in terms of task requirement. Perhaps analysis of usage trends inclusive of the most senior category, ignored in this study, could have supported the suggestion by Vandenbosch and Huff (1997) since the scope of decision tasks would have been widened by this inclusion.

A surprising outcome was the insignificant empirical difference among the categories of age on all the variables of the study. The influence of age on IT usage has been shown, dating back to studies such as the one by Zmud (1979) from which it was suggested that young IT users behave differently from old IT users towards the adoption of IT. Current studies still suggest the view that age has a significant impact on usage intention (Burton-Jones and Hubona, 2006), with younger users more inclined to use technologies than older users. The similarity in behaviour across age categories could have been due to fact that the BI domain at SA-Bank seldom changes, thus allowing old users sufficient time to adjust between new BI change initiatives. The authors (Burton-Jones and Hubona, 2006) also reflected in their findings that education has a positive effect on IT usage. At SA-Bank, however, education had no impact on usage. Perhaps knowledge acquired through formal education plays no role in this organisation, but experience acquired with the length of service in this institution. Or it could also be that the decision tasks require no additional knowledge from users other than the direct interpretation of data towards decision task completion (Burton-Jones and Hubona, 2006).

Gefen and Straub (1997) & Venkatesh and Morris (2000) mention that differences in gender have varying effects on IT usage. There was, however, no sign of such behaviour on the gender categories of this study. Both studies showed that women are less inclined to familiarise themselves with new technology, while man were keen to adopt or learn new technological features. This study is based on a BI system which has been in place for a long time, suggesting that women at SA-Bank could have long overcome the resistance of adopting a BI system, hence showing behaviour that is similar to their male counterparts.

Lastly, experience is the only group which had observable different behaviours across its categories. As expected, computer self-efficacy appeared to be increasing with the number of years spent using the BI system at SA-Bank (Compeau and Higgins, 1995). Further analysis showed that the relation between experience and the decision task characteristics (DT) construct was contrary to findings of past IS studies (Venkatesh and Morris, 2000). Users at SA-Bank found their decision tasks to lack clarity and more dependent on colleague interaction as they gained more experience on the BI system. This could be attributed to failure of the BI system to meet the changing business need (over time) or a limitation in functionality of the BI system which becomes more visible as users gain knowledge of both the system and the business environment in which they operate (Venkatesh and Morris, 2000).

4.6 Factor analysis

Following Hair *et al*.'s (2010) guideline for deriving a factor solution in research, principal component analysis was performed with SPSS version 18, and confirmatory factor analysis was performed with the partial least squares software application, SmartPLS version 2.0.

4.6.1 Principal component analysis (PCA)

One of the required conditions for factor analysis, correlation, was satisfied as per the analysis of sub-section 4.4.6. Furthermore, other required conditions of exploratory factor analysis were performed after the first output of PCA with Varimax rotation was computed from SPSS. The Bartlett's test of Sphericity was statistically significant, indicating factorability of the correlation matrix of this study (Moon and Kim, 2001) and the Kaiser-Meyer-Olkin value was 0.891 showing adequate sampling (Pallant, 2007 & Moon and Kim, 2001). In addition, adequate sampling was inspected with the analysis of the ratio of sample to variable. This ratio exceeded the minimum of 5:1 at 7:1 given an absolute sample size of 174 and 7 variables (Hair *et al*., 2010). To a reasonable degree of error all the necessary assumptions were met for a PCA analysis to be performed.

Analysis of a Varimax rotated matrix indicated that PU items loaded significantly (above 0.45) on one factor where DBF items loaded the highest and on another factor where only PU items loaded. Thus these items were removed and factor analysis was computed again (Hair *et al*., 2010). A convincing structure emerged after all BIS items were removed in addition to the deletion of PU items, following similar reasoning of cross-loading analysis. A latent root criterion method showed that the data represented a 4 factor solution (with eigenvalues greater than 1) explaining 72.4% of total variance. Analysis of the scree test plot (see

Appendix H), however, indicated the possibility of a five factor solution. Therefore, risking an error of inclusion, five factors were forced with a Varimax rotation to obtain a solution which explained 79.6% of total variance (Straub, Boudreau and Gefen, 2004). The five scales were analysed for reliability and the outcome suggested that better reliabilities for factors 3 and 5 (in Table 2 below) could be obtained if items IU1 and DT4 were removed. PCA was recomputed taking this suggestion into account and 82.9% of total variance was explained by factors made up of the remaining items. Table 2 shows the results of a PCA with Varimax rotation (which converged after 6 iterations). Items loaded high on their respective factors, thereby showing unidimensionality (Hair *et al.*, 2010). By reflecting unidimensionality, the constructs had also indicated both convergent and discriminant validity (Gefen *et al.*, 2000). Also shown in Table 2 are the Cronbach's alphas for the 5 scales which resulted from PCA. The magnitudes indicated that the scales are reliable with values above the 0.7 threshold given in quantitative IS studies (Straub *et al.*, 2004).

Table 2: Varimax rotated component matrix [a]

Variable	**Factor**				
	1	2	3	4	5
DBF1	**.811**				
DBF2	**.810**				
DBF3	**.801**				
DBF4	**.714**				
CSE1		**.896**			
CSE2		**.830**			
CSE4		**.820**			
PEOU2			**.742**		
PEOU3			**.792**		
PEOU4			**.796**		
IU2				**.855**	
IU3				**.839**	
IU4				**.807**	
DT1					**.820**
DT2					**.798**
Cronbach's Alpha	.907	.821	.919	.925	.812

[a] Items, BIS2, CSE3, DT3,IU1, PEOU1 and PU1 were not considered due to PCA analysis and data abnormality explained in the data cleaning section.

4.6.2 Confirmatory factor analysis (CFA)

CFA was shown applying three approaches, one approach to determine convergent validity and two approaches for discriminant validity. Convergent validity was shown with the analysis of factor loadings of related items. Meanwhile discriminant validity was shown with the analysis of item cross-loadings, and average variance extracted (AVE) together with the construct correlation matrix. The research model of the study was created in SmartPLS without items BIS2, CSE3, DT3, IU1, PEOU1 and PU1 for reasons explained in the data cleaning and exploratory factor analysis sections above.

Table 3: Loadings and cross-loadings of the measurement model [a]

Variables	BIS	CSE	DBF	DT	IU	PEOU	PU
BIS1	**0.768**	0.039	0.545	0.449	0.417	0.501	0.496
BIS3	**0.812**	-0.111	0.600	0.524	0.439	0.513	0.616
BIS4	**0.856**	-0.197	0.666	0.548	0.523	0.613	0.665
CSE1	-0.112	**0.798**	-0.106	-0.077	-0.087	-0.307	-0.160
CSE2	-0.050	**0.843**	-0.062	-0.049	-0.074	-0.232	-0.155
CSE4	-0.155	**0.805**	-0.168	-0.188	-0.095	-0.191	-0.174
DBF1	0.687	-0.154	**0.894**	0.536	0.599	0.621	0.726
DBF2	0.669	-0.156	**0.912**	0.499	0.676	0.650	0.759
DBF3	0.699	-0.091	**0.870**	0.504	0.561	0.628	0.693
DBF4	0.693	-0.177	**0.868**	0.565	0.630	0.635	0.762
DT1	0.560	-0.184	0.544	**0.869**	0.581	0.501	0.641
DT2	0.603	-0.168	0.563	**0.873**	0.545	0.544	0.620
IU2	0.502	-0.054	0.569	0.525	**0.878**	0.528	0.633
IU3	0.557	-0.158	0.644	0.552	**0.938**	0.643	0.741
IU4	0.527	-0.113	0.631	0.597	**0.916**	0.593	0.732
PEOU2	0.631	-0.304	0.679	0.477	0.629	**0.927**	0.734
PEOU3	0.617	-0.386	0.585	0.547	0.567	**0.906**	0.649
PEOU4	0.608	-0.289	0.592	0.461	0.569	**0.886**	0.654
PU2	0.677	-0.218	0.711	0.643	0.705	0.666	**0.921**
PU3	0.687	-0.160	0.747	0.655	0.742	0.649	**0.947**
PU4	0.686	-0.167	0.773	0.550	0.707	0.764	**0.850**

[a] Items, BIS2, CSE3, DT3,IU1, PEOU1 and PU1 were not considered due to PCA analysis and data abnormality explained in the data cleaning section.

The PLS algorithm was then executed to generate factor loadings. The item loadings of related items were above the threshold of 0.7 suggested by Gefen et *al*. (2000) & Straub *et al.* (2004). The outcome of CFA, shown in Table 3, reflected high loadings of related items and no sign of serious cross loadings. Significance testing with the SmartPLS bootstrapping algorithm indicated that the t-values are greater than the critical value (±1.96), which suggested that all items loaded statistically significantly on their respective constructs. Thus discriminant validity was exhibited by all analysed scales.

Table 4: Correlation of latent constructs and the square root of AVE

Variable	Mean (STD)	Composite Reliability	BIS	CSE	DBF	DT	IU	PEOU	PU
BIS	5.160 (1.195)	0.894	**0.824**						
CSE	2.549 (1.391)	0.895	-0.148	**0.825**					
DBF	5.710 (1.076)	0.936	0.775	-0.164	**0.887**				
DT	5.074 (1.078)	0.821	0.631	-0.154	0.594	**0.738**			
IU	5.812 (1.060)	0.936	0.609	-0.132	0.697	0.645	**0.887**		
PEOU	5.604 (1.098)	0.932	0.694	-0.297	0.715	0.545	0.664	**0.880**	
PU	5.641 (1.178)	0.951	0.751	-0.207	0.830	0.692	0.800	0.759	**0.910**

Table 4 shows among other values (discussed shortly) the composite reliability of constructs, which according to Gefen *et al*. (2000) is the Fornell and Larcker's (1981) equivalent measure to Cronbach's alpha. Magnitudes of composite reliabilities were well above the threshold of 0.7 suggested by Park and Keil (2009), an indication that the scales were reliable measures of what they were theoretically assigned to measure. Also shown in this Table 4 are the mean scores and standard deviations for each scale as derived from SPSS version 18. The square root of AVE with latent construct correlation criterion also suggested that all scales have discriminant validity (see bold figures in Table 4 below). This result is evidenced by the fact that the square root of AVE for any specific construct is greater than that of correlated magnitudes. Worth noting was the similarity between the PCA and CFA structures. Even though both convergent and discriminant validity were evident from the outcome of CFA, Table 3 reflected high correlations between BIS and DBF, and DBF and PU a result which has seen BIS and PU items removed from principal component analysis.

4.7 Non-bias test outcomes

A 'Response time' control group was created to separate early respondents from late respondents. All responses received within the first week of study administration were grouped as early respondents and the rest as late respondents. Early respondents therefore constituted 58% (N = 101) of responses, while late respondents made up the balance of 42% (N = 73). A MANOVA analysis was performed with response time as an independent variable. Box's M test and the Levene's test, both used to assess homogeneity of variance, did not reflect violation of this assumption for the response time groups, 'week 1' and 'week 2 to 3', both showing sig. < 0.001 and sig. > 0.05 respectively (Pallant, 2007). Analysis of a MANOVA then indicated that there was no significant difference between early and late respondents, Wilks's Lambda = 0.943, $p = 0.382$, thereby suggesting that the study was free of non-response bias.

A Harmon's single factor test indicated significant effects of common method-bias, because the first factor in PCA analysis accounted for more than 50% of total variable variance (Podsakoff *et al*., 2003). As an additional validation approach, a common factor was created and added to the measurement model in PLS. The change in variance explained was 0%, an indication of non-method bias according to Zhang and Watts (2008). With the contrasting results, common method-bias (CMV) appears to be a concern in the study even though one method, the common method factor, showed a positive result. There is, however, limited documentation about the second method in IS literature and it is only used in this study for its ease of execution. On the other hand, the Harmon's single factor is known for weaknesses which could have negatively influenced the findings of the CMV test in this study, one being lack of precision (Malhotra, Kim and Patil, 2006). Overall, the CMV tests performed in this study resulted in an inconclusive outcome.

4.8 Hypotheses testing

4.8.1 PLS analysis

The hypotheses were tested using PLS with all constructs modelled as reflective variables (Straub *et al.*, 2004). A sample of 174 entries was used for this analysis. This sample size exceeded the recommended sample size required for a PLS analysis (Gefen *et al.*, 2000). The final structure of a CFA was computed to generate output to test the hypotheses of the study. The results of the analysis are summarised in Figure 5 below. Standardised coefficients are shown on the paths of the diagram with corresponding t-values in brackets.

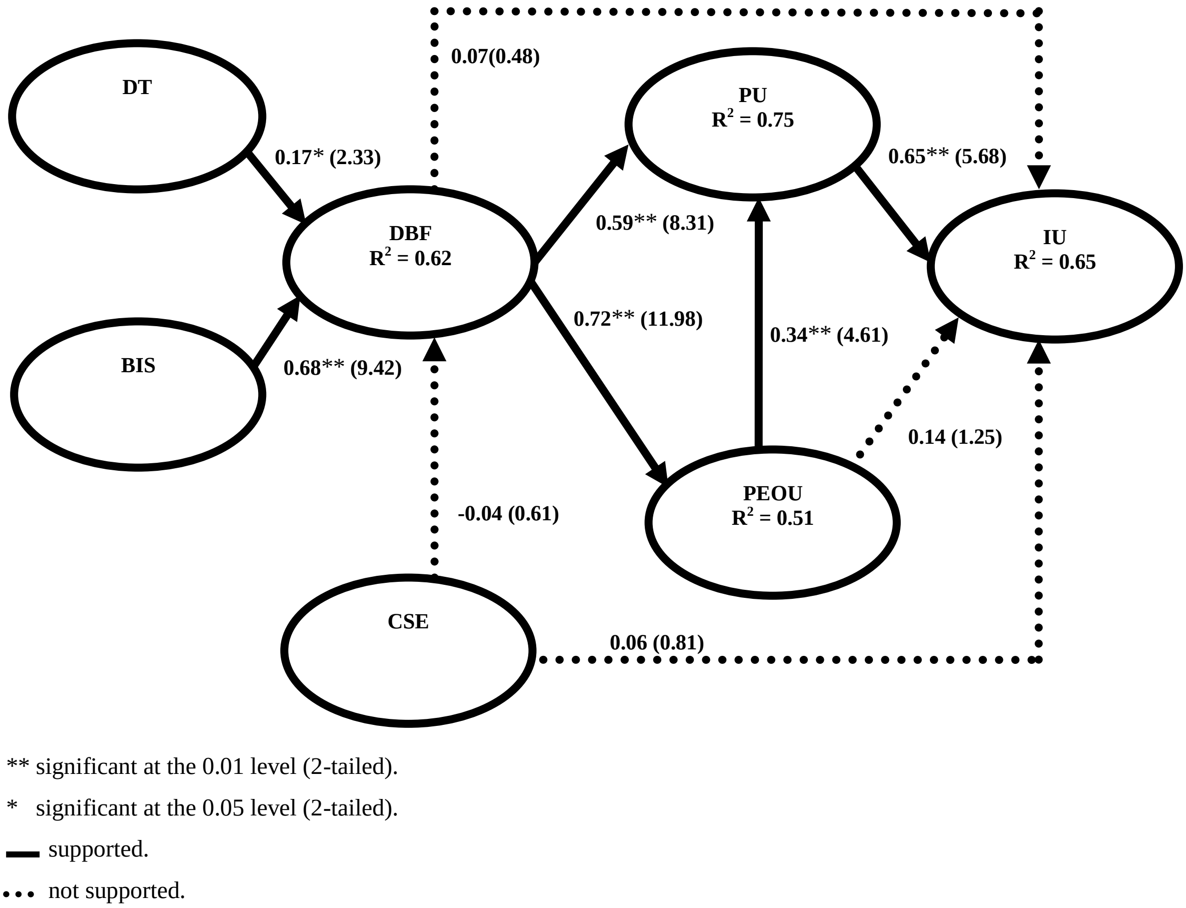


Figure 5: Results of PLS analysis

The determinants proposed in this study of BI system usage predicted 65% (R^2 = 0.65) of intention to use (IU) a BI system at SA-Bank, an improved prediction when compared to past similar IS studies (Strong, *et al.*, 2006 & Dishaw and Strong, 1999). Of the four theoretically proposed predictors, DBF (β = 0.07, t = 0.48), CSE (β = 0.06, t = 0.81), PU (β = 0.65, t =

5.68) and PEOU (β = 0.14, t = 1.25), of IU only PU was statistically significant, supporting hypothesis H2. The non-significance of the impact on IU of DBF, PEOU and CSE indicated lack of support for hypothesis H4a, H1 and H5b respectively. Furthermore, PU was significantly affected by PEOU (β = 0.34, t = 4.61) and DBF (β = 0.59, t = 8.31), thereby supporting hypotheses H3 and H4b respectively. Both predicted 75% (R^2 = 0.75) of the perceived usefulness of the BI system at SA-Bank. DBF (β = 0.72, t = 11.98) explained 51% (R^2 = 0.51) of perceived ease of use, an indication of support for hypothesis H4c. 62% of the variance in DBF was explained by CSE (β = -0.04, t = 0.6111.98), DT (β = 0.17, t = 2.33) and BIS (β = 0.68, t = 9.42), an indication of support for hypotheses H6 and H7 and lack thereof for hypothesis H5a.

4.8.2 Regression analysis

A standard multiple regression was performed for two models as follows: One: DBF, PU and PEOU as independent variables of IU, a dependent variable. Two: DT and BIS as independent variables and DBF as a dependent variable. After a preliminary analysis, of linearity with P-P plots, and homoscedasticity with residual scatterplots, no violation of these assumptions was detected for both proposed models (see Appendix I & Appendix J for the histograms and scatterplots of both models respectively). The tolerance and variance inflation factor (VIF) magnitudes did not indicate any serious problems of multicollinearity, tolerance values were greater than 0.1 and VIF less than 10 (Hair *et al*., 2010). The results of the two regressed models are shown in Table 5 below. On the first model, the three factors explained 57% of IU, $F(3, 173) = 38.46$, $p < 0.05$ with only PU impacting significantly on IU. When DBF was considered separately it significantly explained 43% of IU, β = 0.657, t = 11.44 and sig. < 0.05. Furthermore, PEOU assessed as the only independent variable to IU explained 36%, β = 0.597, t= 9.763 and $p < 0.05$. A test to determine whether DBF and PEOU have independent individual effects on PU was positive, with DBF still appearing to be a stronger predictor of PU than PEOU. Analysis of the second regression reflected that 61% of DBF was explained by DT and BIS, $F(2, 173) = 132.52$, $p < 0.05$.

Table 5: Multiple regression results

Dependent Variable	Independent Variable	R^2	β	t-statistic	Sig.	Mean	STD
IU		0.57				5.84	1.080
	PEOU		0.098	1.326	0.187	5.57	1.142
	DBF		0.098	1.082	0.281	5.69	1.089
	PU		0.598	6.083	0.000	5.63	1.480
DBF		0.61					
	DT		0.212	10.270	0.000	4.98	1.337
	BIS		0.630	3.453	0.001	5.18	1.890

4.8.3 Summary of hypothesis testing

Table 6 below summarises the hypothesis testing outcome from PLS. Of the 10 hypotheses proposed in the theoretical section of the study, six were supported. An unusual outcome was the lack of support for H1, which deviated from most past quantitative IS research (Venkatesh and Davis, 2000 & Igbaria *et al*., 1995). Also uncommon in quantitative IS research was the unsupported paths between DBF and IU, and CSE and IU. Dishaw and Strong (1999) found that the fit between a computer system and task has a significant impact on the intention to use a computer, while Strong *et al*. (2006) have later shown that computer self-efficacy does the same to the intention to use.

Table 6: Hypothesis test summary

Research Model Path	Hypothesis	Outcome
PEOU => IU	H1	Unsupported
PU => IU	H2	Supported
PEOU => PU	H3	Supported
DBF => IU	H4a	Unsupported
DBF => PU	H4b	Supported
DBF => PEOU	H4c	Supported
CSE => DBF	H5a	Unsupported
CSE => IU	H5b	Unsupported
DT => DBF	H6	Supported
BIS => DBF	H7	Supported

4.9 Conclusion

The chapter covered the discussion of all statistical examinations performed for the study. Beginning with data normality checks, the data collected was found to deviate from univariate normality rules. Parametric tests were still performed, however, because multivariate normality was satisfied by the data. The findings of hypothesis testing as reflected by the main analysis technique of the study, PLS, reflected that 60% of the paths in the research model were supported while the rest did not lend support. This result was supported by linear regression analysis with which discrete analysis of relationships was also performed. This analysis of individual relationships suggested that except for CSE, all the factors proposed to be determinants of intention to use were statistically significant.

CHAPTER 5: DISCUSSION

5.1 Overview

This chapter discusses the results of data analysis presented in chapter four in light of the theoretical framework of the study. In this discussion, the outcome of data analysis is linked back to the three objectives listed below, which were first introduced in Chapter One of the study:

- What are the combined decision task and BI system characteristics that lead to BI system usage?
- What are the user capability characteristics that influence BI system usage?
- What are the beliefs that influence decision makers to use a BI system?

Each variable making the research model of the study is discussed individually, specifically assessing the confidence with which scales (measuring these variables) can be regarded as valid and reliable, and the meaning of relationships among constructs in light of BI system usage determinants at SA-Bank. A summary of factors and their order of importance are thereafter outlined, because the aim of the study was to assess determinants of BI system usage. Finally, taking all discussion covered in the chapter into account, a conclusion is presented.

5.2 Validity and reliability

The scales reflected an outcome which did not deviate significantly from past IS studies. Guided by scale validity and reliability thresholds recommended for IS studies in Hair *et al*. (2010); Gefen *et al*. (2000) & Straub *et al*. (2004), this outcome also suggested that the scales were both reliable and valid with the exception of decision task characteristics (DT). More on the reliability and validity of DT is covered in the discussion of this scale below. Therefore, the extent to which the context of this study differed from other contexts where the same scales had been applied successfully, this outcome extends validation of the scales in the context of SA-Bank.

Common method variance, which is measurement error due to collecting data of both the dependent and the independent variables at one point in time (Malhotra and Grover, 1998), resulted in inconclusive findings, which therefore limited the certainty that the results were indeed subjected to insignificant measurement error. Non-response bias, which is the distortion of findings due to withdrawal from study of participants who share common characteristics, was not violated, indicating that respondents could have been representative of the sample (King and He, 2005).

5.3 The dependent variable – Intention to use

The scale outcome reflected that BI users at SA-Bank are inclined to increase their use of the BI system in the near future. This extends the suggestion that the system has always been viewed in a positive light within the firm.

The model of the study explained 65% of the variance of intention to use a BI system, an above average explanation when contrasted to past IS studies (Burton-Jones and Hubona, 2006; Gefen and Straub, 1997 & Venkatesh and Morris, 2000). Such a high value could be attributed to applying the model to study a BI system which is a problem solving aid by design. This follows from Goodhue’s (1998) three step view of problem solving: user conception of a problem; user development of a mental belief about the capability of the system and a user decision whether to (or not to) engage the technology to solve the problem. The model applied in this study captured the capability of the BI system such that users were enabled to judge on system capability in light of decision problems. Such measurement (of both system and task) was indeed inevitable for the investigation of this study, where users were extremely depended on aggregated data from a decision support system to complete decision tasks. So the degree to which the BI system was useful or easy to use was assessed based on the function and outlook of a technology which was synonymous with task execution or problem solving. Thus the improved explained variance could imply that the model matched a study where a technology is an integral part of problem solving. Dishaw and Strong (1999) demonstrated that a measure of the alignment of computer system and task was a significant factor towards determining whether a system is useful or is easy to use. This further suggested that a measure which focuses on technology and task enhances the measurement of technology use, better still for a setting such as that of SA-Bank because of the high dependence of users on decision support systems. Finally, although this result is higher than commonly seen in IS studies, it is nevertheless comparable to a few available studies such as Cheng (2011) which reflected a variance of 64% explained for IT usage. This study was similar to Cheng's (2011) study in that it focused on specific system features like response time and output quality, towards IS adoption, but differed in that it was based on constructs derived from three theoretical frameworks. Therefore, another reason high variance was explained in this study could be that users were able to identify with the BI system qualities that were analysed, that is, the investigated system features overlapped to a certain extent with the actual features possessed by the BI system at SA-Bank.

The intention to use a BI system correlated significantly with all the other variables of the study, and the strongest correlation was with perceived usefulness (PU). This result was consistent with the outcome of regression analysis where PU was the only variable exerting a significant direct effect on BI system usage over the perceived decision task – BI system fit (DBF), the perceived ease of use (PEOU) and computer self-efficacy (CSE). A similar effect of PU on the intention to use a technology has been shown in Venkatesh and Davis (2000) & Wixom and Todd (2005) among other studies in IS. Thus validation of the relationship between the two constructs, perceived usefulness and intention to use, was extended for a BI system. This outcome highlighted that BI system usage strongly depended on a system which enhanced performance of decision tasks and/or which delivered information that was pertinent to user requests, PU. BI system usage still depended on the alignment of the system to decision tasks (DBF) and the ease with which the system was operable (PEOU), because they reflected a significant effect in the absence of PU, while computer self-efficacy remained insignificant even in this case. The overall outcome of the assessment of factors with direct effects on IU, however, contradicts the hypothesis that, CSE, DBF and PEOU are all factors in the presence of perceived usefulness, also an uncommon finding in IS (Wixom and Todd, 2005 and Strong *et al*., 2006). Nonetheless, the lack of influence of the three factors could be explained following trends related to their application in IS research. DBF was reported by Dishaw and Strong (1999) to overlap with perceived usefulness (PU), a likely cause of the weak impact it reflected on IU in this study. Perceived ease of use was reported in IS research to exert a significant impact on IU, but the effect was lower than that shown on perceived usefulness (Venkatesh and Davis, 2000). Thus the strength of the relationship between usefulness and IS usage shown in IS adoption implies that the effect of PEOU on the intention to use a BI system is subsumed by the effect of PU as a co-factor. This is also evidenced by the high correlation between perceived usefulness and perceived ease of use. Finally, computer self-efficacy (CSE), the perceived ability of using a technology (Compeau and Higgins, 1995), is dependent on the usage attitude in the environment of adoption as much as on how it influences technology usage (Thong *et al*., 2004). The high usage reflected by the variance explained in this study, imply that users were not bothered by their ability to operate the BI system, resulting in the insignificance of CSE.

5.4 Independent variables to IU (*Direct effects*)

5.4.1 Perceived usefulness (PU)

Consistent with the suggestion that the model deployed in this study suited the nature of the study, a higher variance than reported in past IS studies was obtained for PU (Wixom and Todd, 2005 & Chau and Hu, 2002). This variance was significantly explained by two factors, decision task – BI systems fit (DBF) and perceived ease of use (PEOU), proposed to have direct effects on PU. This outcome indicated that the perceived usefulness of the BI system at SA-Bank depended on how easy it was to operate its functions, and the extent to which it aligned to decision tasks. In other words, the BI system required no additional effort from users other than what was necessary to complete decision tasks, and it satisfied user information requests. The greater influence of DBF, however, implied that ensuring the system meets the needs of decision tasks was more important to the BI user community than simplifying user interaction with the system. It was still important, however, that users execute decision tasks with minimum effort possible, given that PEOU still had a significant impact on the usefulness of a BI system.

A search of top IS journals resulted in no BI study found which could be used as comparison with the findings of this study. The closest study to the investigation performed was by Wixom and Todd (2005), who showed that the satisfaction of users on the quality of information of a data-warehouse has a significant and higher influence on PU than exerted by the ease of using a system. In their study, the authors surveyed organisations which had data warehouse systems that were already functional. The results came close to the variance of PU explained in this study, but information satisfaction was used instead of DBF. Therefore, to the degree which DBF as measured in this study compared to information quality as measured by Wixom and Todd (2005), this study extended validation of the determinants of PU within the SA-Bank context.

5.4.2 Perceived ease of use (PEOU)

PEOU was predicted by only one independent variable, namely decision task – BI systems fit (DBF). Mathieson and Keil (1998) performed a similar study to assess the effect that DBF has on the perceived ease of use. Similar to the findings of this study, the outcome of their investigation showed that DBF was a significant predictor of PEOU, although with lesser variance explained than in the present study. Therefore, this study extended validation that DBF predicts the extent to which a system is easy to use, implying that at SA-Bank BI users believed that the system was easy to use because it met the needs of BI executable tasks. This is also the same view shared by Goodhue and Thompson (1995) that the effort a user spends on completing tasks, PEOU, depends on the fit between system functions and task needs. The difference in variance explained between the two studies could have been caused by a similar suggestion that the model applied in this study suits a BI study.

PEOU reflected an insignificant influence on the intention to use a BI system, thus not lending support to the hypothesis that it is a factor of BI system usage. As the only factor to BI system usage, however, the assessment outcome reflected that it was a significant factor. It is thus an important factor of BI system usage on its own. Supporting the same view is Vessey and Galletta (1991) who stated that decision makers have limited capacity for processing information towards making decisions, because more information than can be processed with a human mind is normally input to decision making. Thus users are induced to search for alternatives in an attempt to reduce the effort required by the process of decision problem execution. Put in other words, whenever a user is faced with a decision problem, as much as it will induce a search for a solution, the user also seeks to resolve the decision task with the lowest effort possible. PEOU was thus a necessary requirement for BI system usage. In the SA-Bank context it meant that, even though users were inclined to use a system because it enhances performance of decision tasks (PU) over the view that it required minimum effort during performance of tasks (PEOU) they, however, would still use a system for only offering the benefits of PEOU. In BI terms, minimum effort, could translate to extracting data with the least necessary set of keyboard strokes or mouse clicks, and data processing that minimises duplication of effort.

5.4.3 Perceived decision task – BI system fit (DBF)

BI users at SA-Bank reported reasonable satisfaction about the degree to which the BI system qualities matched decision task profiles. For this construct, items could not be stated without capturing the essence of ease of use, of usefulness and of system adequacy (Dishaw and Strong, 1999). Thus DBF highly correlated with perceived ease of use, perceived usefulness and BI system characteristics, hinting a potential overlap between DBF and these mentioned constructs.

It was not surprising that the three independent variables of DBF namely, computer self-efficacy (CSE), decision task characteristics (DT) and BI system characteristics (BIS) also predicted a variance higher than seen in past IS studies (Lin and Huang, 2008 & Strong *et al*., 2006). Firstly, it is implied in Vessey and Galletta (1991) that CSE, DT and BIS are all important determinants of the perceived fit between task and technology. Secondly, at SA-Bank decision tasks and technology are inseparable at the level of usage (diagnostic usage) considered in this study. Thus the improved variance could have been influenced by the simultaneous effect of proposing correct determinants for DBF and applying measures that befitted the setting of SA-Bank.

Two independent variables, decision task characteristics and BI system characteristics, exerted a significant influence on DBF, with computer self-efficacy (CSE) being the only insignificant predictor. This result was consistent with the low correlation that was observed between CSE and DBF. Contrary to this result Strong *et al*. (2006) & Lin and Huang (2008) have shown that CSE has a significant impact on DBF. The reported high rate of BI system usage at SA-Bank, however, could have positively influenced user capability towards the BI system, because behaviour from the environment positively affect computer self- efficacy (Compeau and Higgins, 1995; Gallivan *et al.*, 2005 & Thong *et al*., 2004).

Consistent with past IS studies (Lin and Huang, 2008 & Goodhue and Thompson, 1995) the decision task characteristics (DT) and BI system characteristics (BIS) impacted significantly on the perception of BI system and decision task fit (DBF). Emphasising this point is Vessey and Galleta (1991) who suggested that presenting graphical data to users has different consequences to delivering tabulated output, depending on user information needs. These authors state that a user will comprehend a technology data presentation format that corresponds to his/her mental framework of the likely solution for the decision problem. The outcome of DBF determinants therefore extended validation of the task technology fit model for the BI system usage study.

5.4.4 Computer-self efficacy (CSE)

The scale result has shown that SA-Bank employees are able to execute decision tasks without help from BI technicians or user manuals. The importance of CSE in IS adoption has been shown in many settings and for many technologies (Lin and Huang, 2008; Strong *et al.*, 2006 & Gallivan *et al.*, 2005). Contradicting effects of CSE on usage were, however, found in this study.

Computer self-efficacy (CSE) was expected to have a significant effect alongside the perceived usefulness (PU) towards determining BI system usage, because of similar evidence in past IS research (Strong *et al.*, 2006). CSE, however, it neither showed a significant impact on BI system usage nor on perceived decision task – BI system fit (DBF), even when considered as the only factor to both the intention to use a BI system (IU) and DBF. Further analysis reflected that the relationship between CSE and IU was consistent with the hypothesised relationship between the two constructs in this study, that is, users capable of executing the functions of the BI system would be inclined to use the system, while those who are incapable would be disinclined to use it. Given that the effect was statistically insignificant, however, implied that SA-Bank users were not concerned about their ability to operate the BI system. One factor which could have contributed to CSE being a non-factor was the positive attitude of users towards the BI system at SA-Bank. Users are likely to learn to use a system from colleagues in an environment where the dominant attitude is positive use (Gallivan *et al.,* 2005). Another factor which could have also contributed to the insignificant effect of CSE on IU was the length of time for which the system had existed at the time of study (Koufaris, 2002). Users are likely to be anxious about their ability to use a technology during the first few days of being exposed to it, while such anxiety is likely to diminish with successive encounters (Compeau and Higgins, 1995). Even though it is tempting to include the length of existence of the BI system at SA-Bank as another factor contributing to the insignificance of computer self-efficacy (CSE), the lack of knowledge of how CSE would have influenced BI usage when the system was first implemented, made this suggestion inconclusive.

5.5 Independent variables to IU (*Indirect effects*)

5.5.1 Decision task characteristics (DT)

Only two items, DT1 & DT2, remained from a data reduction exercise performed in Chapter Four. The two items were related to the dimension of task-routineness as given by Goodhue and Thompson (1995). In addition, the scale formed by these two items was a significant predictor of decision task – BI systems fit (DBF). A similar result was suggested by Ling and Huang (2008) who has shown that the task-routineness dimension of DT was a significant determinant of a knowledge management system. The fact that only two items formed the DT scale in this study, however, suggested the possibility that the applied scale could have an error of exclusion, because other aspects of task-routineness could have been omitted (Churchill, 1979). Nonetheless, the degree to which properties of decision task characteristics were captured by the DT scale, its validation was extended in this study. The outcome of this scale suggested that users at SA-Bank executed decision tasks that are unstructured and non-routine. Worth noting is that DT has also shown a high correlation with IU, a hint that it could be another direct factor of BI system usage.

5.5.2 BI system characteristics (BIS)

If the collected data are anything to go by, a conclusion can be drawn that the system at this organisation possessed qualities which to a certain extent aligned to the executed decision tasks. Moreover, analysis of statistical outcome indicated that this variable is the most important predictor of the fit between task and technology (DBF) for the BI system at SA-Bank. This finding was consistent with past research (Wixom and Todd, 2005 & Lin and Huang, 2008). At SA-Bank, the BI system was reflected to be that which responded quickly to data request, was often available, had functions which could be adjusted to meet new business demands and presented users with reliable data. These qualities were more appropriate for decision task profiles that are unstructured and non-routine. As with decision task characteristics, BIS had a high correlation with IU, hinting at a possibility that it could have a direct effect on BI system usage as well. In addition, BIS also showed a high correlation with PU, indicating that it also could have a direct effect on the perceived usefulness of a BI system.

5.6 Putting it all together

With the context of generalising the findings limited to the bounds of SA-Bank and the technology of focus being a BI system, the study resulted in the following outcomes as guided by the objectives of the study:

- Objective 1, the decision task characteristics were identified to be non-routine and unstructured, and the corresponding BI system characteristics were identified to be quick response to data request, consistent availability, flexibility and reliability.
- Objective 2, none of the investigated BI user capabilities appeared to influence BI system usage.
- Objective 3, perceived usefulness, perceived ease of use and the perceived alignment between decision task and technology all positively impacted on BI system use. Although when all were considered at once, perceived usefulness was the only variable to influence BI system usage significantly, however, they all had a significant influence when considered individually. The order of the magnitude of influence which they exerted on BI system usage followed the sequence in which they are listed.

Figure 6 below summarises the outcome of hypothesis testing performed in this study. Only paths which were statistically significant are considered to suggest a model that could be applied for further assessment of BI system usage determinants.

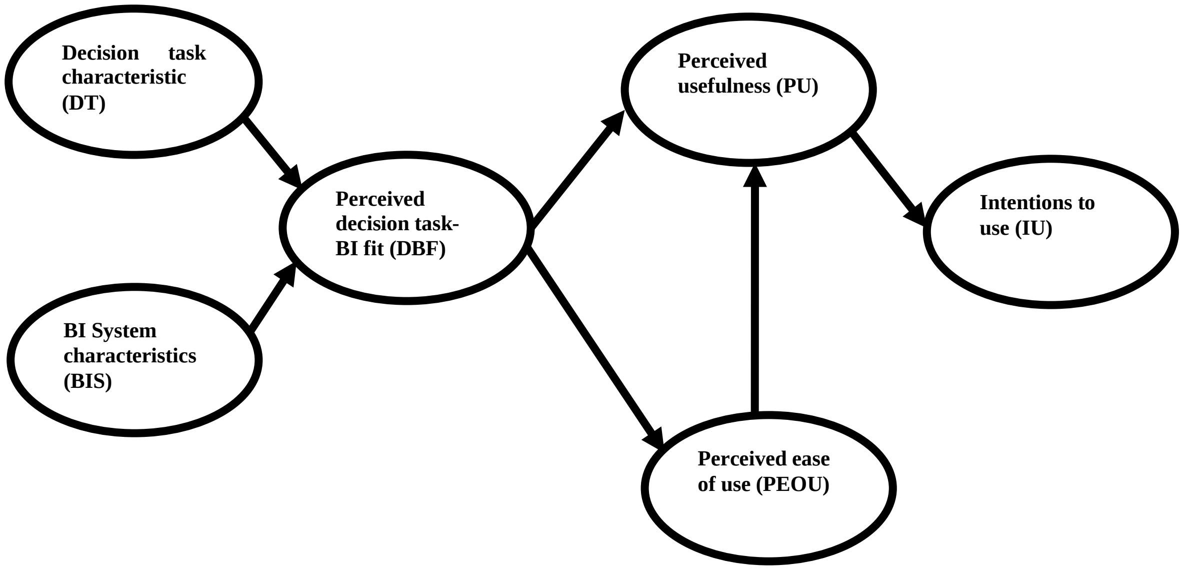


Figure 6: Revised model

5.7 Conclusion

The chapter discussed the variables of the study, specifically looking at the scale reliability and validity in contrast to past IS research. Building towards the goal of giving answers to the questions stated as objectives of the study, the relationships between these variables were analysed in light of the findings of Chapter Four. This culminated in perceived usefulness being identified as a critical belief for BI system usage. This belief construct was predicted significantly by the alignment of decision task and the BI system, suggesting that DBF should be achieved as a first condition towards BI system implementation.

CHAPTER 6: CONCLUSION

6.1 Overview

This chapter concludes the study by mapping the discussion of the findings to the identified gap in IS research. The benefits accruing to both academia and practice are stated, while highlighting areas in IS research which, if covered, promise to complement the extension of knowledge achieved in this study. The discussion of the chapter is thus sub-divided into the summary of the study, the contribution to theory, limitations, suggested further research and managerial guidelines and, finally concluding remarks.

6.2 Summary of the study

The limited knowledge on business intelligence in the IS domain motivated this study with primary focus on identifying factors which influenced BI system usage within SA-Bank. The study applied constructs backed by three theoretical frameworks, task technology fit (TTF), technology acceptance model (TAM) and social cognitive theory (SCT), to measure the influence of BI system usage factors. Consistent with the tradition of cumulative knowledge in the positivist paradigm, the research domain upon which this study is based, the study intended to advance IS knowledge by the application of the constructs from the three theoretical frameworks in a physical context, a financial firm – SA-Bank, together with a technological context, a BI system. Thus IS knowledge extension was achieved by applying these constructs in a seldom mentioned context in IS studies, which combines a financial institution and BI technology (Petrini and Pozzebon, 2009; Lawton, 2006 & Lönnqvist and Pirttimäki, 2006). Even though the identification of the determinants for BI system usage was the main aim of the study, of equal importance was the investigation of the BI phenomenon in the SA-Bank context.

The data collected for the study exceeded the minimum number of responses required for partial least squares (PLS) analysis, a data analysis technique applied in this study. Furthermore, a data reduction exercise resulted in all proposed scales in this study being retained for statistical analysis. These scales were also measured with the recommended minimum of three items (Churchill, 1979) with the exception of decision task characteristics (DT), suggesting that except for DT the scales employed a greater likelihood of correctness in measuring BI system properties (Malhotra and Grover, 1998). Analysis outcome reflected that of all the proposed factors, only computer self-efficacy (CSE) was non-influential as a determinant of both BI system usage, and the fit between BI system and decision task (DBF). Only the usefulness of a BI system reflected significant impact on usage when all the factors were considered together. Nevertheless, each one of the factors, perceived usefulness, perceived ease of use, decision task – BI system qualities fit, excluding the non-significant CSE, have shown significant impact when considered as the only determinants, a reflection that they were all important determinants of BI system usage. The usefulness of a BI system was in turn influenced by the fit between decision task and BI system (DBF) and perceived ease of use (PEOU), emphasising that DBF and PEOU were mandatory factors of usage, though they only had strong indirect effects when assessed alongside perceived usefulness as a factor.

6.3 Contribution to research and theory

The application of the technology acceptance model (TAM) and task-technology fit (TTF) in a merged form was shown in IS research to possess more strength for predicting technology usage in many settings than when either model was considered individually (Dishaw and Strong, 1999; Mathieson and Keil, 1998 & Pagani, 2006). Guided by such findings, the study investigated the validity of the linked-up model for a BI system, an unusual approach for BI technology investigations according to the outcome of literature review performed in this study. Better still was the incorporation of the computer self-efficacy construct (CSE) to the linked-up (TAM and TTF) model, a strategy that was motivated by the intention to analyse qualities attributable to the social aspect of SA-Bank. As far as the literature review of this study is concerned, very few studies applied the set of constructs as exploited here, despite a combined assessment of the constructs for their IT usage prediction strength, suggesting that they could complement one another for investigations similar to the one performed in this study. A better explanation of usage was indeed obtained, possibly an indication of the strength of the model. The narrow context of the study, however, limited generalising the results across settings. Nonetheless, the high predicted variance of BI system usage hinted that there could be theoretical value in joining the constructs towards studying a BI system as performed in this study. For this reason the study extended validation of a model (of joined theoretical frameworks) which further IS research can explore to enrich IS knowledge on BI system usage.

Additionally, the study context, SA-Bank, extended the range of settings which were exploited in IS research prior to performance of this study. The context of SA-Bank in light of the findings of the study also forms a basis upon which financial institutions in South Africa can advance the knowledge of business intelligence. Finally, the methodological approach adapted from Gefen (2002) of backing PLS analysis with regression analysis, suggests that more insight could be discovered by this analysis approach. This can be evidenced by the fact that some constructs (such as the perceived ease of use) which appeared to be non-factors with PLS became significant factors with regression analysis.

6.4 Limitations of study

Limitations were identified as stated concisely in this discussion. Using e-mail to administer the study could have resulted in coverage error, an error arising due to reaching out to only a portion of the intended potential participants (Sivo, *et al.*, 2006). Surveys are known for wide area coverage in research (King and He, 2005), but there was however no guarantee that every characteristic of the population at SA-Bank was covered with the survey distribution technique of this study. One limitation therefore is inherent in relying on the assumption that every aspect of influence on the investigation of this study was captured by the study method from the SA-Bank population. Nonetheless, whether the above was the case needed a separate and independent sample from that which was analysed in this study, an exercise which could not be afforded due to resource and time constraints. Internal validity, the degree to which the change of the dependent variable is caused by a corresponding change on the independent variable (Malhotra and Grover, 1998), could not be assured by this study alone. A study which is only performed by gathering data at a single point in time is likely to only be showing the existence of correlation among factors and not causation (Gefen, 2002). Thus the causal links depicted in the research model of the study still remain hypothetical. Also, according to this author, the use of a self-reported measure may have contributed to the high variance explained in this study. Furthermore, the revised model could be applicable to only the type of usage, diagnostic usage, investigated in this study and it could also be valid in settings where the condition of usage is non-mandatory as is the case at SA-Bank. Finally, the use of e-mail to gather responses could have skewed the results, because the origin of these responses was not traced.

6.5 Future research

The revised research model needs to be piloted in other financial institutions in South Africa in order to verify whether it equally applies in these institutions. This could enable a conclusion to be drawn about the relationship between the model and financial institutions in general. Perhaps a trend could also emerge which enables organisations spanning space and industries to utilise this solution. Research is also needed to verify whether the model equally applies to organisational contexts that can be differentiated by the brand of technology which they apply for business execution. SA-Bank, for example, applied Oracle technologies for all business operation that was related to IT processing, and thus further research was needed to investigate the dependence/independence of the model to the type of technology upon which a BI system is based. Moreover, there was a need to study whether the model is only applicable to usage of an in-house developed BI solution as is the case at SA-Bank, or whether it also applies to usage of turnkey BI solutions, that is, BI solutions that are purchased off an IT vendor's shelf.

Research is needed to verify whether the revised research model of this study also applies to tactical, evaluative and strategic usage types discussed in Chapter Two, or even so in settings where the BI system is used for multiple strategic foci. This model is a high level framework which requires further refinement in order to be converted into practical significance with ease. Thus research, which focuses on the individual components of the model, could bring to light information which enables this framework to be put to practice with minimal effort. For instance, a reference to time was made in one of the measurement items for BI system characteristics (BIS), 'the BI system quickly responds to my data requests'. Therefore, further studies should focus on quantifying some of the factors inherent in words which are subjective in nature, such as the word, 'quickly', used above. Last, but not least, is the fact that CSE has been widely shown to be a significant determinant of IT. In this study, however, it was found to be a non-factor with the reason for its lack of influence attributed to the effects of high environmental usage of the BI system on individual users, and the length of time for which the BI system has existed. Whether a similar outcome would be obtained for a new BI system is thus a subject for future research.

6.6 Managerial guidelines

The study confirms the importance of the perceived usefulness and the perceived ease of use towards using a technology. Over half of the variance of intentions to use a BI system was explained by the perceived usefulness of the system, an indication that BI design should primarily focus on delivering relevant information to designated users. This is important because of two reasons. Firstly, BI systems process data that resides in a data warehouse, that is, a data store keeping data from all transactional systems within a firm, thus identifying which user should get what information is inevitable. Secondly, a BI system supplies varying levels of aggregated data to users, therefore the importance of allowing users to access only information applicable to their business needs is emphasised. The results, however, corroborated this view but more studies are needed to generalise it across settings. On the other hand, the perceived ease of use did not show a significant influence on the intention to use a BI system in light of the perceived usefulness, but was a significant determinant of the perceived usefulness. Thus, the outlook of the interface and the performance of functions also contribute to the user judgement that a BI system is useful. Therefore, it should go without mention that the interface of a BI system should be consistent in outlook with other business technological interfaces with which users are familiar. BI functions should offer flexibility such that users are able to access the whole range of data residing in the data warehouse that is relevant to their needs. Moreover, these functions should be tuned to minimise processing time of user requests.

What is perceived usefulness and perceived ease of use of a BI system? What should be done in order to increase these factors? To answer the first question, these two can be associated with the perception that applying a BI system enhances performance of tasks and in just the time necessary to do so. Apparently, the type of decision tasks and the quality of the BI system have direct influence on these user perceptions. Users commonly dealing with non-routine decision tasks, or in a frequently changing business environment, should consider investing in a BI system with the following qualities: quick response time, high availability, high flexibility and high reliability.

6.7 Conclusion

This study contributes to IS knowledge by increasing understanding of how factors which are known to affect IT usage in the IS domain affect usage of the BI system at SA-Bank. The influence of BI systems information is increasingly dominating non-academic IS article sources such as Gartner Inc. and Information Management, while top academic IS journals are not growing by an equivalent information pack. This study, however, suggested a model which if further exploited promises to positively affect knowledge advancement of BI systems both academically and practically. This model suggests that BI system usage is determined by the perceived usefulness of a BI system, which in turn is positively affected by the perceived ease of use and perceived decision task – BI system fit.

References

Argawal, R. and Karahana, E. (2000). Time flies when you are having fun: Cognitive absorption and beliefs about information technology use. *MIS Quarterly* 24(4):665:694

Bailey, K.D. (1994). Methods of Social Research (4th Ed.). Free Press, New York, NY

Bernroider, E.W.N. (2008). IT governance for enterprise resource planning supported by the Delone-Mclean model of information success. *Information & Management* 45:257:269.

Bowman, B.J. (2002). Building knowledge management system. *Information Systems Research* 19(3):32:40

Burton-Jones, A. and Hubona, G.S. (2006). The mediation of external variables in the technology acceptance model. *Information and Management* 43(2006):706:717

Chan, Y.E. and Huff, S.L. (1992). Strategy: an information systems research perspective. *Journal of Strategic Information Systems* 1(4):191:202

Chau, P.Y.K. (1996). An empirical assessment of a modified technology acceptance model. *Journal of Management Information Systems* 13(2):185:204

Chau, P.Y.K. and Hu, P.J. (2002). Examining a model of information technology acceptance by individual professionals: An exploratory study. *Journal of Management Information Systems* 18(4):191:229

Chen, L., Soliman, K.S., Mao, E. and Frolick, M.N. (2000). Measuring User Satisfaction with Data Warehouses: An exploratory study. *Information and Management* 37(3):103:110

Cheng, Y. (2011). Antecedents and consequences of e-learning acceptance. *IS journal* 21:269:299

Churchill, G.A., Jr. (1979). A Paradigm for Developing Better Measures of Marketing Constructs. *Journal of Marketing Research* 16(1):64:73

Compeau, D., Higgins, C.A. and Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS Quarterly* 23(2):145:158

Compeau, D.R. and Higgins, C.A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly* 19(2):189:211

D'Ambra, J. and Rice, R.E (2001). Emerging factors in user evaluation of the World Wide Web. *Information & Management* 38:373:384

Davis, F.D (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13(3): 319:340

Dayal, U., Castellanos, M., Simitsis, A., Wilkinson, K. (2009). Data integration flows for business intelligence. *Communication of the ACM*

DeLone, W. H. and McLean, E.R. (1995). Information systems success: the quest for dependant variables. *Information systems research* 3(1):60:95

Dennis, A.R. and Reinicke, B.A. (2004). Beta versus VHS and the acceptance of electronic brainstorming technology. *MIS Quarterly* 28(1):1:20

Dennis, A. R., Wixom, B. H., & Vandenberg, R. J. (2001). Understanding Fit and Appropriation Effects in Group Support Systems via Meta-Analysis. *MIS Quarterly* 25(2):167:193

DeSanctis, G. and Poole, M.S. (1994). Capturing the complexity in advanced technology use. *Organisation Science* 5(2)

Dishaw, M.T. and Strong, D.M. (1999). Extending the technology acceptance model with task-technology fir constructs. *Information & Management* 36:9:21

Doll, W.J., Hendrickson, A. and Dong, X. (1998). Using Davis's perceived usefulness and ease of use instruments for decision making: A confirmatory and multigroup invariance analysis. *Decision Sciences* 29(4):839:869

Easley, R.F., Devaraj, S. and Crant, J.M. (2003). Relating collaborative technology use to team work quality and performance: An empirical analysis. *Journal of management information systems* 19(4):247:268

Elbashir, M.Z., Collier, P.A., and Davern, M.J. (2008). Measuring the effects of business intelligent systems: The relationship between business process and organisational performance. *International journal of accounting information systems* 9:135:153

Fornell, C., D. F. Larcker. 1981. Evaluating structural equation models with unobservable variables and measurement error. *J. Marketing* 18(1):39:50.

Galliers, R.D. and Newell, S. (2003). Back to the future: from knowledge management to the management of information and data. *Information Systems and e-Business Management* 1:5:13.

Gallivan M.J., Spliter, V.K. and Koufaris M. (2005). Does information training really matter? A social information processing analysis of coworkers' influence on IT usage in the workplace. *Journal of Management Information Systems* 22(1):153:192

Gefen, D. (2002). Customer loyalty in e-commerce. *Journal of the Association for Information Systems* 3:27:51

Gefen, D. and Straub, D. (2005). A practical guide to factorial validity using pls-graph: tutorial and annotated example. *Communication of the Association for Information Systems* 16:91:109.

Gefen, D. and Straub, D.W. (1997). Gender differences in the perception and use of e-mails: An extension to the task technology model. *MIS Quarterly* 21(4):389:400

Gefen, D., Karahanna, E. and Straub, D.W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly* 27(1):51:90

Gefen, D., Straub, D.W. and Boudreau, M. (2000). Structural equation modelling and regression: guidelines for research practice. *Communications of AIS* 4(7)

Golfarelli, M., Rizzi, S. and Cella, L. (2004). Beyond data warehousing: what's next in business intelligence? *ACM Conference on Information and Knowledge Management*.

Goodhue, D.L. (1998). Development and measurement validity of a task-technology fit instrument for user evaluations of information system. *Decision Sciences* 29(1):105:138

Goodhue, D.L. and Thompson, R.L. (1995). Task-technology fir and individual performance. *MIS Quarterly* 19(2):213:236

Grewal, R., Cote, J.A. and Baumgartner, H. (2004). Multicollinearity and measurement error in structural equation models: Implications for theory testing. *Marketing Science* 23(4):519:529

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (2010). Multivariate data analysis (7^{th} Ed.). Upper Saddle River: Pearson/Prentice Hall

Hsu, M. and Chiu, C. (2004). Internal self-efficacy and electronic service acceptance. *Decision Support Systems* 38:369:381.

Human Science Research Council (2011). HSRC code of research ethics. Retrieved June 29, 2011, from http://www.hsrc.ac.za/index.php?module=pagesetter&func=viewpub&tid=132&pid=168

Igbaria, M., Guimaraes, T. and Davis, G.B. (1995). Testing the determinants of microcomputer usage via a structural equation modelling. *Journal of Management Information Systems* 11(4):87:114

Jarvenpaa, S.L., Shaw, T.R. and Staples, D.S. (2004). Towards contextualised theories of trust: The role of trust in global virtual teams. *Information Systems Research* 15(3):250:267

Kaplan, B. and Duchon D. (1988). Combining qualitative and quantitative in information systems research: A case study. *MIS Quarterly* 12(4):571:586

Kim, H. and Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: A status quo bias perspective. *MIS Quarterly* 33(3):567:582

King, W.R. and He, J. (2005). External validity in IS research. *Communication of the Association for Information Systems* 16:880:894

Koufaris, M. (2002). Applying the technology acceptance model and flow theory to online consumer behavior. *Information Systems Research* 13(2):205:223

Lawton, G. (2006). Making business intelligence more useful. *IEEE Computer Society* 14:16.

Lee, A.S. and Hubona, G.S. (2009). A scientific basis for rigor in information systems research. *MIS Quarterly* 33(2):237:262

Lee, C., Cheng, H.K. and Cheng, H. (2007). An empirical study of mobile commerce in insurance industry: Task-technology fit and individual differences. *Decision support systems* 43:95:110

Lee, Y., Kozar, K.A. and Larsen, K.R.T (2003). The technology acceptance model: Past present and future. *Communication of the Association for Information Systems* 12(50):752:780

Leidener, D.E. and Elam, J.J. (1995). The impact of organisation information systems on organisation design, intelligence, and decision making. *Organisation Science* 6(6):645:664

Lewis, W., Agarwal, R. and Sambamurthy, V. (2003). Sources of influence on beliefs about information technology use: An empirical study of knowledge workers. *MIS Quarterly* 27(4):657:678

Lin, T. and Huang, C. (2008). Understanding knowledge management systems usage antecedents: An integration of social cognitive theory and task technology fit. *Information and Management* 45:410:417

Little, R. G., Jr. and Gibson, M. L. (2003). Perceived Influences on Implementing Data Warehousing. *IEEE Transactions on Software Engineering* 29(4):290:296

Lönnqvist, A. and Pirttimäki, V. (2006). The measurement of business intelligence. *Information Systems Management* 23(1):32:40

Malhotra, M.K. and Grover, V. (1998). An assessment of survey research in POM: from constructs to theory. *Journal of Operation Management* 16(4):407:425

Malhotra, N.K., Kim S.S. and Patil, A. (2006). Common method variance in IS research: a comparison of alternative approaches and a reanalysis of past research. *Management Science*

Mathieson, K. and Keil, M. (1998). Beyond the interface: Ease of use and task-technology fit. *Information and Management* 34:221:230

Moon, J and Kim, Y. (2001). Extending the TAM for a world-wide-web context. *Information and Management* 38:217:230

Moore, G.C. and Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information system. *Information Systems Research* 2(3):192:222

Negash, S. (2004). Business intelligence. Communications of the Association for Information Systems 13(1):177:195

Nelson, R.R., Todd, P.A. and Wixom, B.H. (2005). Antecedents of information and system quality: An empirical examination within the context of data warehousing**.** *Journal of Management Information Systems* 21(4):199:235

Orlikowski, W.J. and Baroudi, J.J. (1991). Studying information technology in organisations: Research approaches and assumptions. *Information Systems Research* 2(1):1:28.

Pagani, M. (2006). Determinants of adoption of High Speed Data Services in the business market: Evidence for a combined technology acceptance model with task technology fit model. *Information and Management* 43:847:860

Pallant, J. (2007). SPSS survival manual: A step-by-step guide to data analysis using SPSS version 15 (3rd Ed.). McGraw-Hill House

Park, C.W. and Keil, M. (2009). Organisational Silence and Whistle-Blowing on IT Projects: An Integrated Model. *Decision Sciences* 40(4):901:918

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

Phan, D.D. and Vogel, D.R. (2009). A model of customer relationship management and business intelligence systems for catalogue and online retailers. *Information & Management* 47:69:77

Pitt, L.F., Watson, R.T. and Kavan, C.B. (1995). Service quality: A measure of information system effectiveness. *MIS Quarterly* 19(2):173:187

Podsakoff, P. M., MacKenzie, S. B., Jeong-Yeon, L. and Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology* 88(5):879:903

Ramamurthy, K., Sen, A. and Sihna, A.P. (2008). Data warehouse infusion and organisational effectiveness. *IEEE Transaction on system, man, and cybernetics* 38(4):976:994

Rouibah, K. and Ould-ali, S. (2002). PUZZLE: a concept and prototype for linking business intelligence to business strategy. *Journal of Strategic Information systems* 11:133152

Sivo, S.A., Saunders, C., Chang, Q. and Jiang, J.J. (2006). How low should you go? Low response rate and the validity of inference in IS questionnaire research. *Journal of the association for information systems* 7(6):351:414

Srite, M. and Karahanna, E. (2006). The role of espoused national cultural values in technology acceptance. *MIS Quarterly* 30(3):679:704

Straub, D., Boudreau, M. and Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of AIS.*

Straub, D.W. (1989). Validating instruments in MIS research. *MIS Quarterly* 13(2):147:169

Strong, D.M., Dishaw, M.T. and Bandy, D.B. (2006). Extending task technology fit with computer self-efficacy. *The DATA BASE for Advances in Information Systems* 37(2 & 3):92:107

Thong, J.Y.L., Hong, W. and Tam, K.Y. (2004). What leads to user acceptance of digital libraries? *Communication of the ACM* 47(1):79:83

Vandenbosch, B. and Huff, S.L. (1997). Searching and scanning: how executives obtain from executive information systems. *MIS Quarterly* 21(1):81:107

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the task technology model. *Information Systems Research* 11(4):342:365

Venkatesh, V. and Davis F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science* 46(2):186:204

Venkatesh, V. and Morris, M.G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role for technology acceptance and usage behaviour. *MIS Quarterly* 24(1):115:139

Venkatesh, V., Speier, C. and Morris, M.G. (2002). User acceptance enabler in individual decision making about technology: Toward an integrated model. *Decision Sciences* 33(2):297:316

Vessey, I. and Galletta, D. (1991). Cognitive fit: An empirical study of information acquisition. *Information Systems Research* 2(1):63:84

Watson, H.J. and Wixom, B.H. (2007). The current state of business intelligence. *IEEE Computer Society* 96:99

Watson, H.J., Wixom, B.H., Hoffer, J.A., Anderson-Lehman, R. and Reynolds, A.M. (2006). Real-Time Business Intelligence: Best Practices at Continental Airlines. *Information Systems Managemen*t 22(1):7:18

Wixom, B.H. (2004). Business intelligence software for the classroom: microstrategy resources on the teradata university network. *Communications of the AIS* 234:246

Wixom, B.H. and Todd P.A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research* 16(1):85:102

Xu, Z.M., Kaye, G.R. and Duan, Y. (2003). UK executives' vision on business environment for information scanning: A cross industry study. *Information and management* 40:381:389

Yi, M.Y. and Davis, F.D. (2003). Developing and validating an observational learning model of computer software training and skills acquisition. *Information Systems Research* 14(2):146:169

Yu, C. (2003). Toward an understanding of MIS survey research methodology: current practice, trends and implications for future research. *Information and Management Journal* 6(1):39:55

Zhang, W. and Watts, S.A (2008). Capitalising on content: Information adoption in two online communities. *Journal of the Association for Information Systems* 9(3):73:94

Zhong, N., Liu, J. and Yao, Y. (2007). Envisioning intelligent information technologies through the prism of web intelligence. *Communication of the ACM* 50(3):89:94

Zigurs, I. and Buckland, B.K. (1998). A theory of task/technology fit and group support systems effectiveness. *MIS Quarterly* 313:334

Zmud, R.W. (1979). Individual differences and MIS success: A review of the empirical literature. *Management Science* 25(10):966:979

Bibliography

Albert, T. C., Goes, P. B. and Gupta, A. (2004). GIST: A model for design and management of content and interactivity of customer-centric web sites. *MIS Quarterly* 28(2):161:182

Ballou, D. P. and Tayi, G. K. (1999). Enhancing Data Quality in Data Warehousing Environments. *Communications of the ACM* 42(1):73:78

Doll, W.J., Xia, W. and Torkzadeh, G. (1994). A confirmatory factor analysis of the end-user computing satisfaction instrument. *MIS Quarterly* 18(4):453:461

Foshay, N., Mukherjee, A. and Taylor, A. (2007). Does the data warehouse end-user metadata add value? *Communication of the ACM* 50(11):70:77

Gangadharan, G.R. and Swami, S.N (2004). Business intelligence systems: Design and implementation strategies. 26th Int. Conf. Information Technology Interfaces IT1 June 7-10, 2004, Cavtat, Croatia.

Glassey, K. (1998). Seducing the End User. *Communications of the ACM* 41(9):62:69

Goodhue, D., Lewis, W. and Thompson, R. (2007). Statistical power in analysing interaction effects: Question the advantage of PLS with product indicators. *Information System Research* 18(2):211:227

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

Jurison, J. (1996). The temporal nature of IS benefits: A longitudinal study. *Information & management* 30:75:79

Lee, A.S. and Baskerville, R.L. (2003). Generalising generalisability in information systems research. *Information Systems Research* 14(3):221:243

Looney, C.A., Valacich, J.S., Todd, P.A., Morris, M.G. (2006). Paradoxes of on-line investing: Testing the influences of technology on user expectancies. *Decision Sciences* 37(2):205:246

Nicolaou, A.I. and McKnight, D.H. (2006). Perceived information quality in data exchanges: Effects on risk, trust, and intention to use. *Information Systems Research* 17(4):332:351

Sutcliffe, K.M. and McNamara, G. (2001). Controlling decision making practice in organisation. *Organisation Science* 12(4):484:501

Whitten, D. and Leidner, D. (2006). Bringing IT back: An analysis of the decision to backsource or switch vendors. *Decision Sciences* 37(4):605:621

APPENDIX A – QUESTIONNAIRE

Business Intelligence survey

All references to the "BI system" in this survey refer to the BI portal application at SA-Bank.

Section A

In item 1 to 28, Please select the most appropriate choice in light of your BI Portal application experience at SA-Bank (1 refers to **strongly Disagree** and 7 to **strongly Agree**).

1. The functions of the BI system are very adequate.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

2. The functions of the BI are useful.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

3. The capability of the BI system is compatible with my decision task profile.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

4. The functions of the BI system make the performance of decision tasks to be easy.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

5. I often need the BI system to assist me with completing unstructured decision tasks.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

6. I often solve decision problems that are non-routine.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

7. My decision tasks are dependent on me receiving accurate information from colleagues.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

8. I frequently must coordinate my decision task activities with others.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

9. The BI system quickly responds to my data request.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

10. I would give the information provided by the BI system a high rating in terms of quality.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

11. The BI system can flexibly adjust to meet new demands.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

12. The BI system is often available to service my data requests.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

13. Using the BI system improves my performance of decision tasks.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

14. Using the BI system increases my decision making productivity.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	◉

15. Using the BI system increases my decision making effectiveness.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

16. I find BI system to be generally a useful system.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

17. The data presentation format from the BI system is clear.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

18. I find the BI system easy to use.

1 Strongly Disagree	2	3	4	5	6	7 Strongly Agree
○	○	○	○	○	○	○

19. Learning to use new features on the BI system is easy.

1 Strongly Disagree	2	3	4	5	6	7 Strongly Agree
○	○	○	○	○	○	○

20. It's easy to interact with the BI system.

1 Strongly Disagree	2	3	4	5	6	7 Strongly Agree
○	○	○	○	○	○	○

21. I would only be able to use the BI system if there was someone to tell me what to do.

1 Strongly Disagree	2	3	4	5	6	7 Strongly Agree
○	○	○	○	○	○	○

22. I would only be able to use the BI system if I could call someone for help when I get stuck.

1 Strongly Disagree	2	3	4	5	6	7 Strongly Agree
○	○	○	○	○	○	○

23. I would only be able to use the BI system if I had a reference manual.

1 Strongly Disagree	2	3	4	5	6	7 Strongly Agree
○	○	○	○	○	○	○

24. I would only be able to use the BI system if someone showed me what to do first.

1 Strongly Disagree	2	3	4	5	6	7 Strongly Agree
○	○	○	○	○	○	○

25. I will recommend others to use the BI system towards performing decision tasks.

1 Strongly Disagree	2	3	4	5	6	7 Strongly Agree
○	○	○	○	○	○	○

26. I plan to increase my use of the BI system over the next year.

1 Strongly Disagree	2	3	4	5	6	7 Strongly Agree
○	○	○	○	○	○	○

27. I intend to use the BI system at every opportunity over the next year.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

28. I intend to use the BI system as a routine part of my job over the next year.

1	2	3	4	5	6	7
Strongly Disagree						Strongly Agree
○	○	○	○	○	○	○

Section B

In item 29 to 34, Please give one answer for each item.

29. What is the function of your business unit?

30. Which of the following describes your role?
- ◉ Executive
- ○ Senior Manager
- ○ Middle Manager
- ○ Junior Manager
- ○ Other (please specify)

31. Please specify the number of years which you have spent using the BI system:

32. Please select the age range that applies to you.
- ○ 20 to 30
- ○ 31 to 40
- ○ 41 to 50
- ○ 51 to 60
- ○ 60+

33. Please choose the gender description that applies to you.
- ○ Female

- Male

34. What is the highest education level which you completed?

- Completed school
- Completed a skills training course
- Completed a bachelor's degree
- Completed a masters degree
- Completed a PhD degree
- Other (please specify)

Thank you for your consideration to participate in this survey.

Survey link

http://FreeOnlineSurveys.com/rendersurvey.asp?sid=wubwbzzy896d6xt928736

Literature sources of items

Item Code	Descriptions	Agree	Disagree	Author
	Perceived decision task – BI fit (DBF)	1 2 3 4	5 6 7	Lin and Huang (2008)
DBF1	The functions of the BI system are very adequate.			
DBF2	The functions of the BI system are useful.			
DBF3	The capability of the BI system is compatible with my decision task profile.			
DBF4	The functions of the BI			

	system make the performance of decision tasks to be easy.		
	Decision task Characteristics (DT)	1 2 3 4 5 6 7	
DT1	I often need the BI system to assist me with completing unstructured decision tasks.		Goodhue and Thompson (1995)
DT2	I often solve decision problems that are non-routine.		Goodhue and Thompson (1995)
DT3	My decision tasks are dependent on me receiving accurate information from colleagues.		Lin and Huang (2008)
DT4	I frequently must coordinate my decision task activities with others.		Lin and Huang (2008)
	BI System characteristics (BIS)	1 2 3 4 5 6 7	
BIS1	The BI system quickly responds to my data request.		Wixom and Todd (2005)
BIS2	I would give the information provided by the BI system a high rating in terms of quality.		Wixom and Todd (2005)
BIS3	The BI system can flexibly adjust to meet new demands.		Wixom and Todd (2005)
BIS4	The BI system is often available to service my data requests.		Goodhue and Thompson (1995)
	Intension to use a BI system (IU)	1 2 3 4 5 6 7	
IU1	I will recommend others to use the BI system towards performing decision tasks.		Cheng (2011)
IU2	I plan to increase my use of the		Wixom and Todd

	BI system over the next year.		(2005)
IU3	I intend to use the BI system at every opportunity over the next year.		Wixom and Todd (2005)
IU4	I intend to use the BI system as a routine part of my job over the next year.		Wixom and Todd (2005)
	Perceived usefulness (PU)	1 2 3 4 5 6 7	Venkatesh and Davis (2000)
PU1	Using the BI system improves my performance of decision tasks.		
PU2	Using the BI system increases my decision making productivity.		
PU3	Using the BI system increases my decision making effectiveness.		
PU4	I find the BI system to be generally a useful system.		
	Perceived ease of use (PEOU)	1 2 3 4 5 6 7	
PEOU1	The data presentation format from the BI system is clear.		Venkatesh and Davis (2000)
PEOU2	I find the BI system easy to use.		Venkatesh and Davis (2000)
PEOU3	Learning to use new features on the BI system is easy.		Gefen *et al.*(2003)
PEOU4	It’s easy to interact with the BI system.		Gefen *et al.*(2003)
	Computer self-efficacy (CSE)	1 2 3 4 5 6 7	Compeau and Higgins (1995)
CSE1	I would only be able to use the		

	BI system if there was someone to tell me what to do.
CSE2	I would only be able to use the BI system if I could call someone for help when I get stuck.
CSE3	I would only be able to use the BI system if I had a reference manual.
CSE4	I would only be able to use the BI system if someone showed me what to do first.

APPENDIX B – A LETTER TO REUEST PARTICIPATION

Date: 09 August 2011

Good day,

My name is Deane Nkuna, and I am conducting a study in business intelligence (BI) usage determinants.

The study aims to assess factors which impact on the usage of BI system. Therefore, the results will be used towards helping practitioners understand influences to BI system usage. You have been identified as someone who could help in this regard, because of your knowledge on the Wesbank BI environment. I would also appreciate if you could identify colleagues whom you are aware use the BI system, and forward their names to me. These could be people reporting to you or peers.

Should you consider participating in this study, the survey will take you only 15 - 20 minutes to complete. If you would like to know about the findings of the study, please indicate in your response to this request. The results will only be shared in an aggregated format to ensure confidentiality. Again, confidentiality will be further guaranteed by securing the data from unauthorised access via password protection.

Please also note that:

1. By completing this survey you are consenting to your responses being used for research purposes.
2. This survey is completely voluntary and you may choose to exit at any time. All responses will be treated in the strictest of confidence.
3. Should you choose to participate, please answer all questions to the best of your ability and remember that there is no right or wrong answer.
4. Anonymity is ensured by configuring the survey application to disregard respondent identification information.

Thank you for your consideration to participate in this survey.

Regards,

Deane
Tel: (011) 649 5221
E-mail: dnkuna@wesbank.co.za

APPENDIX C – ETHICS CLEARENCE LETTER

UNIVERSITY OF THE WITWATERSRAND
JOHANNESBURG

08th August, 2011

Dear Deane,

Re: STUDENT NAME DEANE NKUNA
STUDENT NUMBER 9411818M

Your Ethics application has been reviewed and the committee has decided to grant your ethics approval pending the following being executed

- The letter for participation must be explicit in "inviting" participation and not "asking" for participation.
- Under does the research expose the participants? You need to say that it in fact does and you need to address how the demographics will be dealt with in this regard.
- Interests with the organisation must be checked for potential conflicts, as you do in fact have an association with the company being researched and you need to explain how you will manage the conflicts.

Please ensure that these changes are implemented by the 15th of August, 2011 to the satisfaction of your supervisor. Please submit a copy of your form, with the changes clearly highlighted to Sibongile Dhladhla. Once your supervisor confirms that your corrections are done (by email to the Chair of the Committee), your Ethics Number will be issued by the Ethics Committee.

Please note you are not allowed to collect data without an Ethics Number being issued.

Regards
Ethics IS Committee

APPENDIX D – COVER LETTER FOR STUDY

Date: 20 August 2011

Good day,

My name is Deane Nkuna, and a few days ago I have sent you a letter asking for your participation in a survey of business intelligence usage determinants. This is a follow up letter to kindly ask you to complete the survey included below as a link.

Your participation will contribute towards a better understanding of factors that determine BI systems design, and thus highly valued.

The survey should take you only 15 - 20 minutes to complete. If you would like to know about the findings of the study, please indicate by forwarding your e-mail address to dnkuna@wesbank.co.za. The results, however, will only be shared in an aggregated format to ensure confidentiality. In addition, confidentiality will be further guaranteed by securing the data from unauthorised access via password protection.

To participate in the survey click on the following link:

http://FreeOnlineSurveys.com/rendersurvey.asp?sid=wubwbzzy896d6xt928736

If the link doesn't open please copy and paste it to the browser's address bar. For any assistance related to the study please call me on my landline: (011) 649 5221, on my cell phone: 0824988470, or my e-mail: dnkuna@wesbank.co.za .

Please also note that:

1. By completing this survey you are consenting to your responses being used for research purposes.
2. This survey is completely voluntary and you may choose to exit at any time. All responses will be treated in the strictest of confidence.
3. Should you choose to participate, please answer all questions to the best of your ability and remember that there is no right or wrong answer.
4. Anonymity is ensured by configuring the survey application to disregard respondent identification information.

Thank you for your consideration to participate in this survey.

Regards,

Deane

Tel: (011) 649 5221

E-mail: dnkuna@wesbank.co.za

APPENDIX E – MISSING VALUE ANALYSIS

Missing value table[a,b]

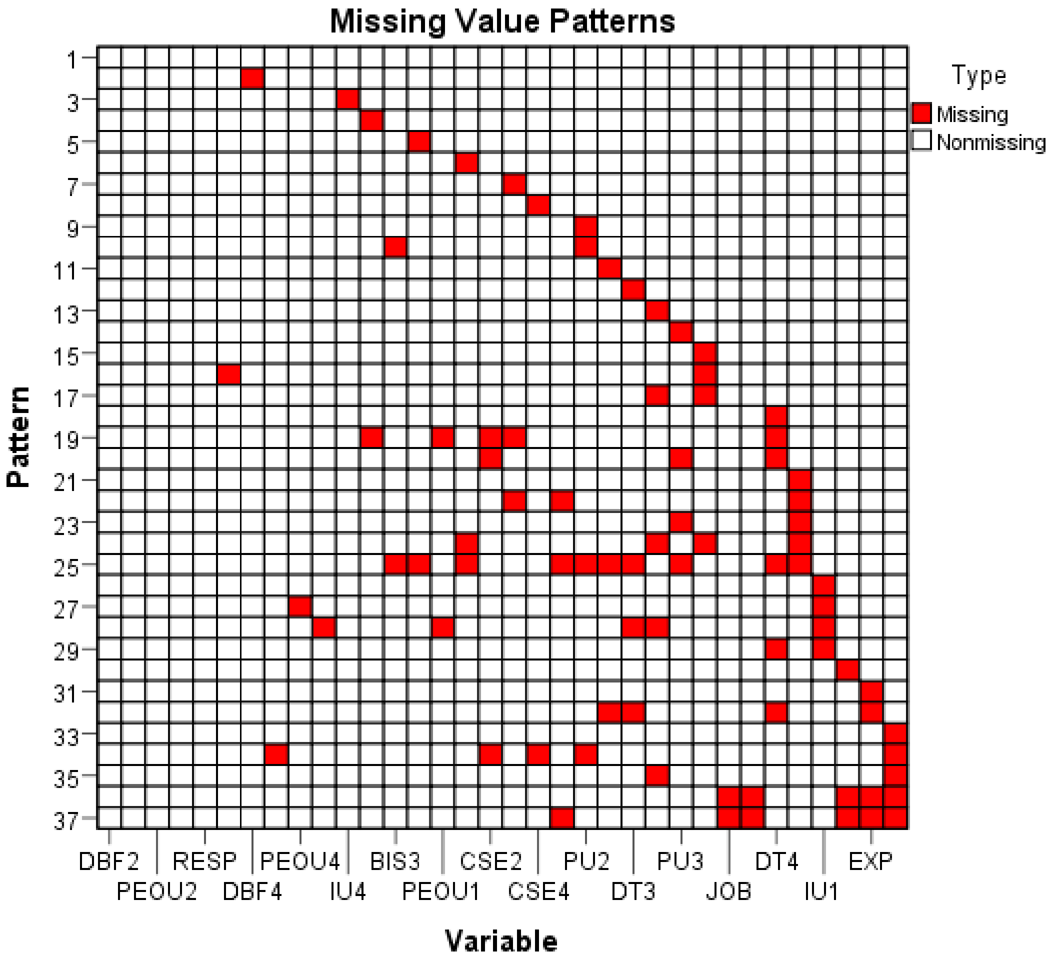
	Missing		Valid N	Mean	Std. Deviation
	N	Percent			
Gender	8	4.5%	171		
BI Experience	8	4.5%	171	4.07	1.972
Age	7	3.9%	172		
Intention to Use1	6	3.4%	173	5.72	1.278
Perceived Usefulness1	6	3.4%	173	5.50	1.319
Decision Task Characteristics4	6	3.4%	173	4.96	1.472
Educational Level	5	2.8%	174		
Job Role	5	2.8%	174		
Intention to Use2	5	2.8%	174	5.74	1.168
Perceived Usefulness3	5	2.8%	174	5.50	1.325
BI System Characteristics4	5	2.8%	174	5.27	1.373
Decision Task Characteristics3	5	2.8%	174	5.31	1.465

Decision Task Characteristics2	5	2.8%	174	4.95	1.533
Perceived Usefulness2	4	2.2%	175	5.47	1.325
Decision Task Characteristics1	4	2.2%	175	4.99	1.480
Computer Self-Efficacy4	3	1.7%	176	2.92	1.896
Computer Self-Efficacy3	3	1.7%	176	2.29	1.508
Computer Self-Efficacy2	3	1.7%	176	2.49	1.670
Perceived Ease of Use3	3	1.7%	176	5.41	1.248
Perceived Ease of Use1	2	1.1%	177	5.68	1.354
Perceived Usefulness4	2	1.1%	177	5.92	1.218
BI System Characteristics3	2	1.1%	177	4.84	1.507
Perceive Decision Task - BI Fit3	2	1.1%	177	5.56	1.256

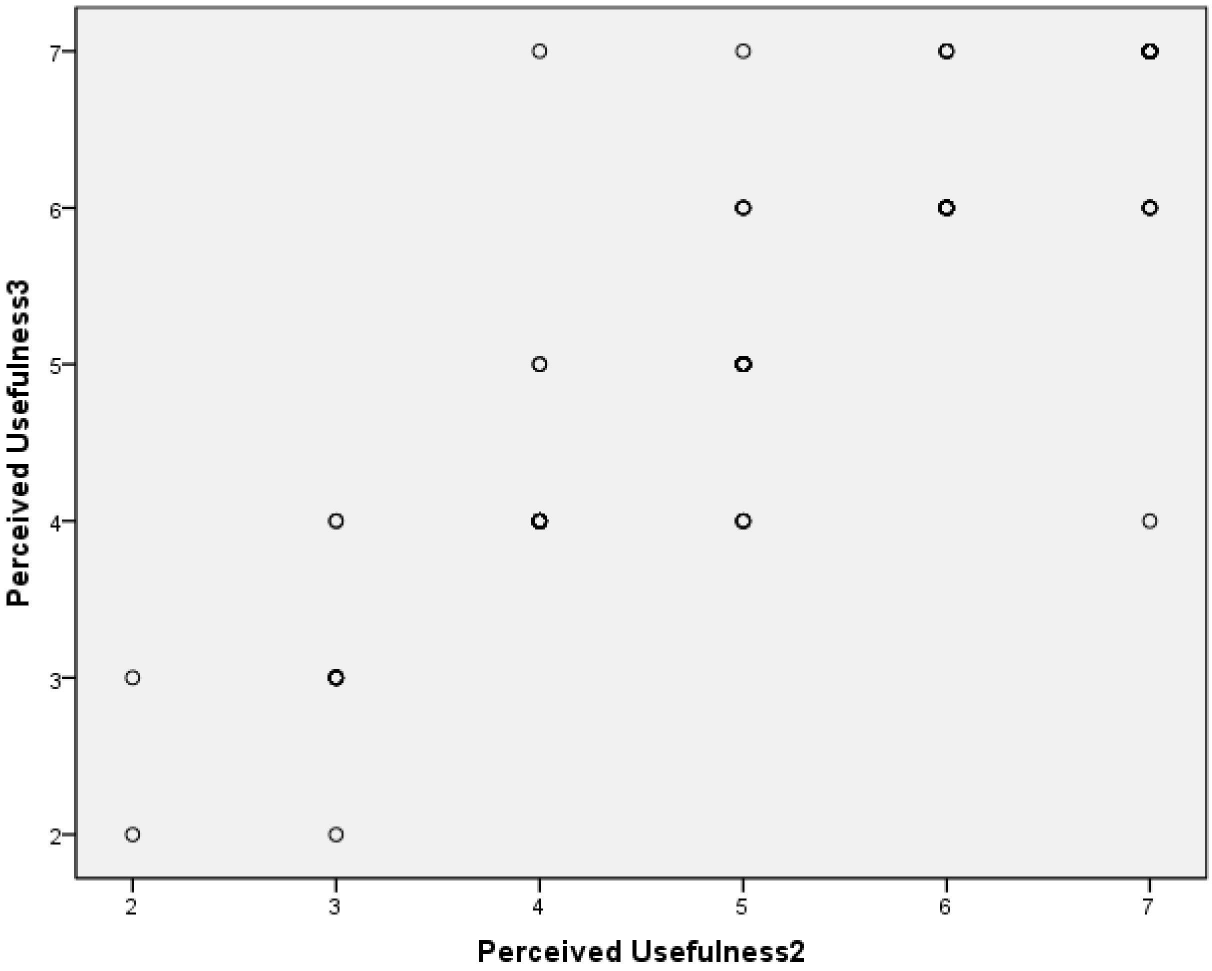
a. Maximum number of variables shown: 25

b. Minimum percentage of missing values for variable to be included: 1.0%

Missing value patterns

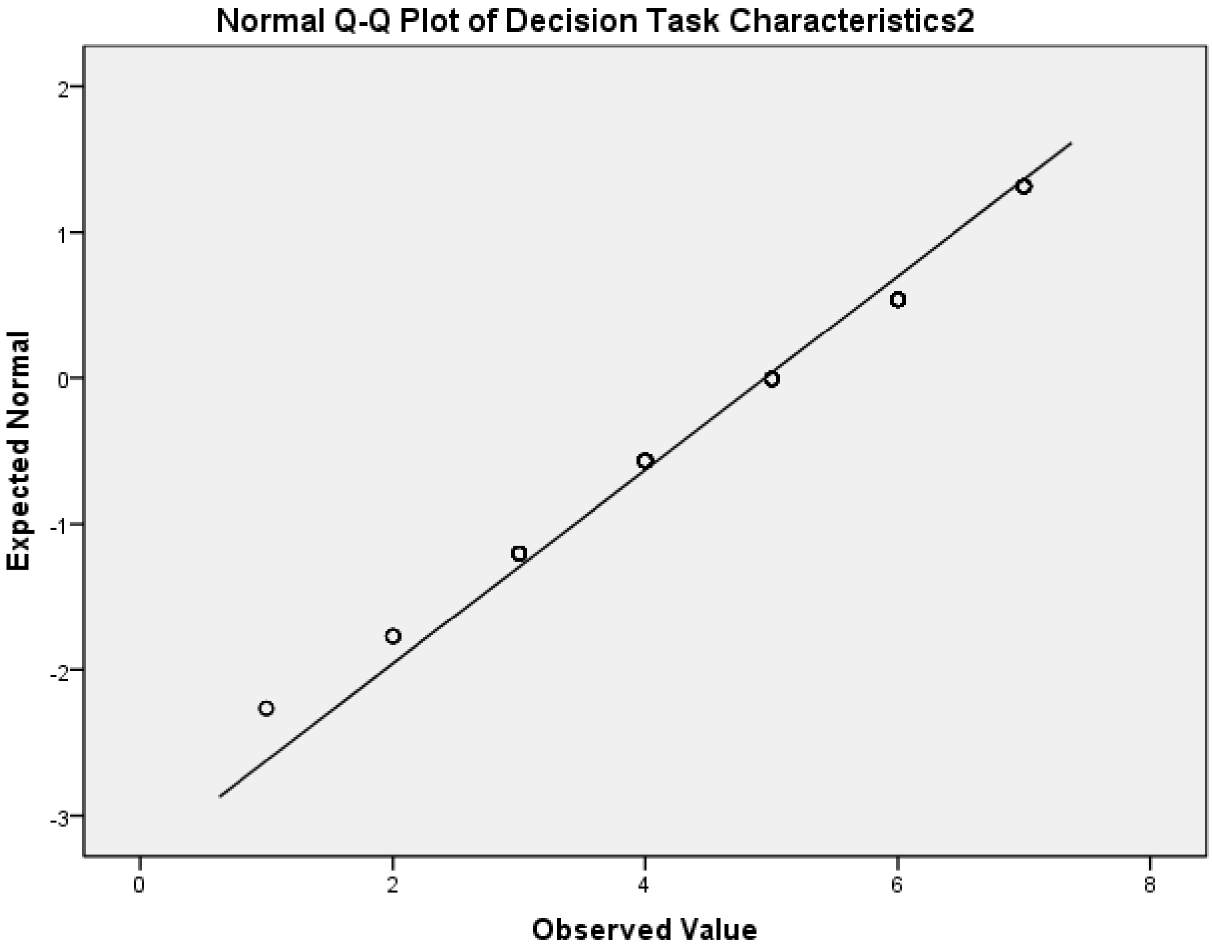


APPENDIX F – MEASUREMENT ITEM SCATTERPLOT

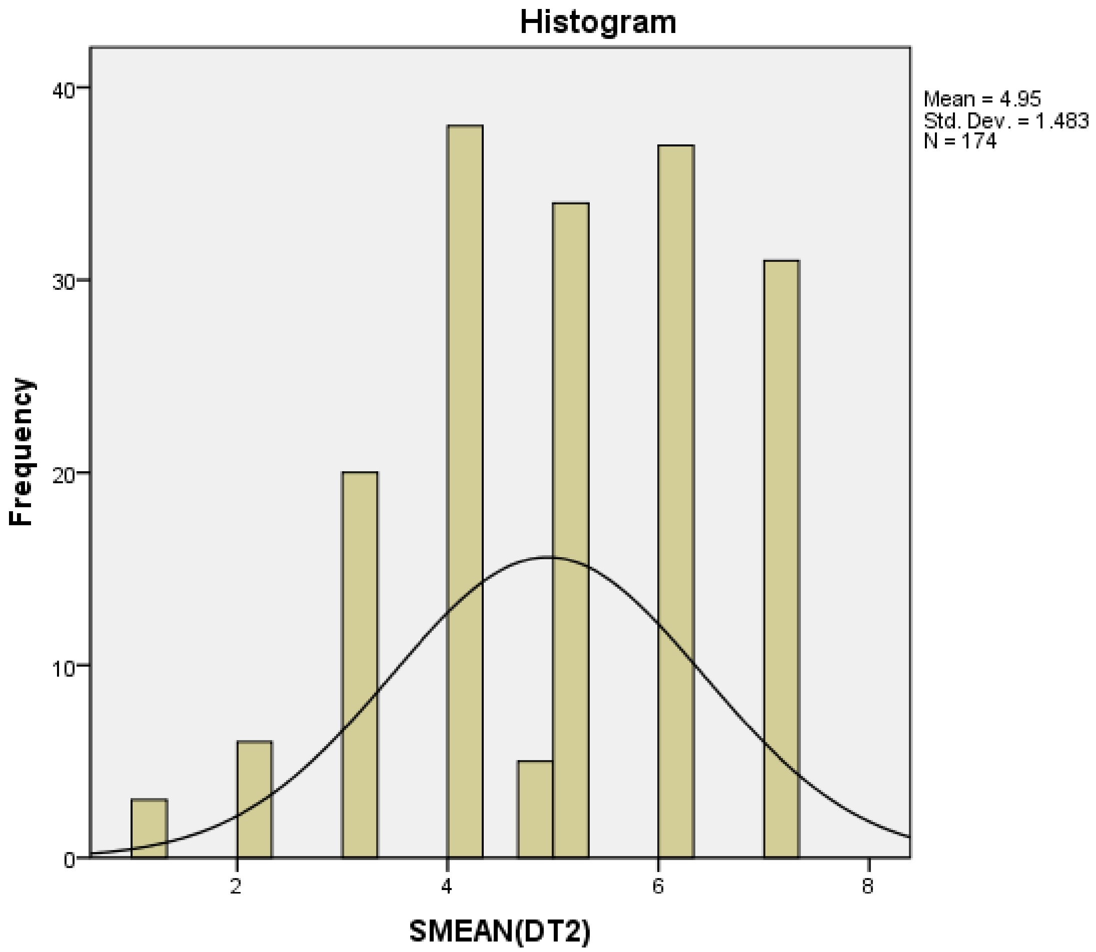


APPENDIX G – MEASUREMENT ITEM NORMALITY

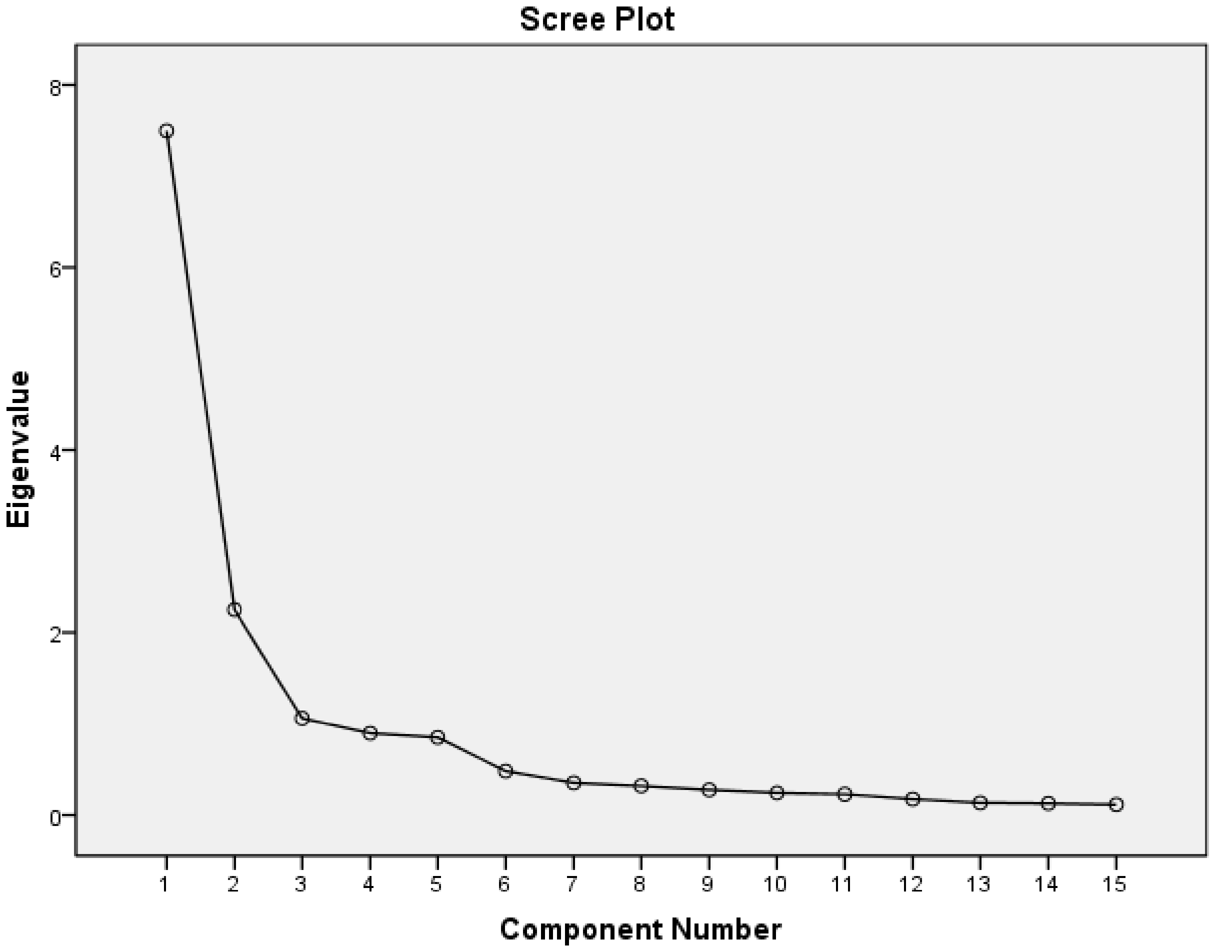
Normal probability plot



Sample histogram (measurement item)

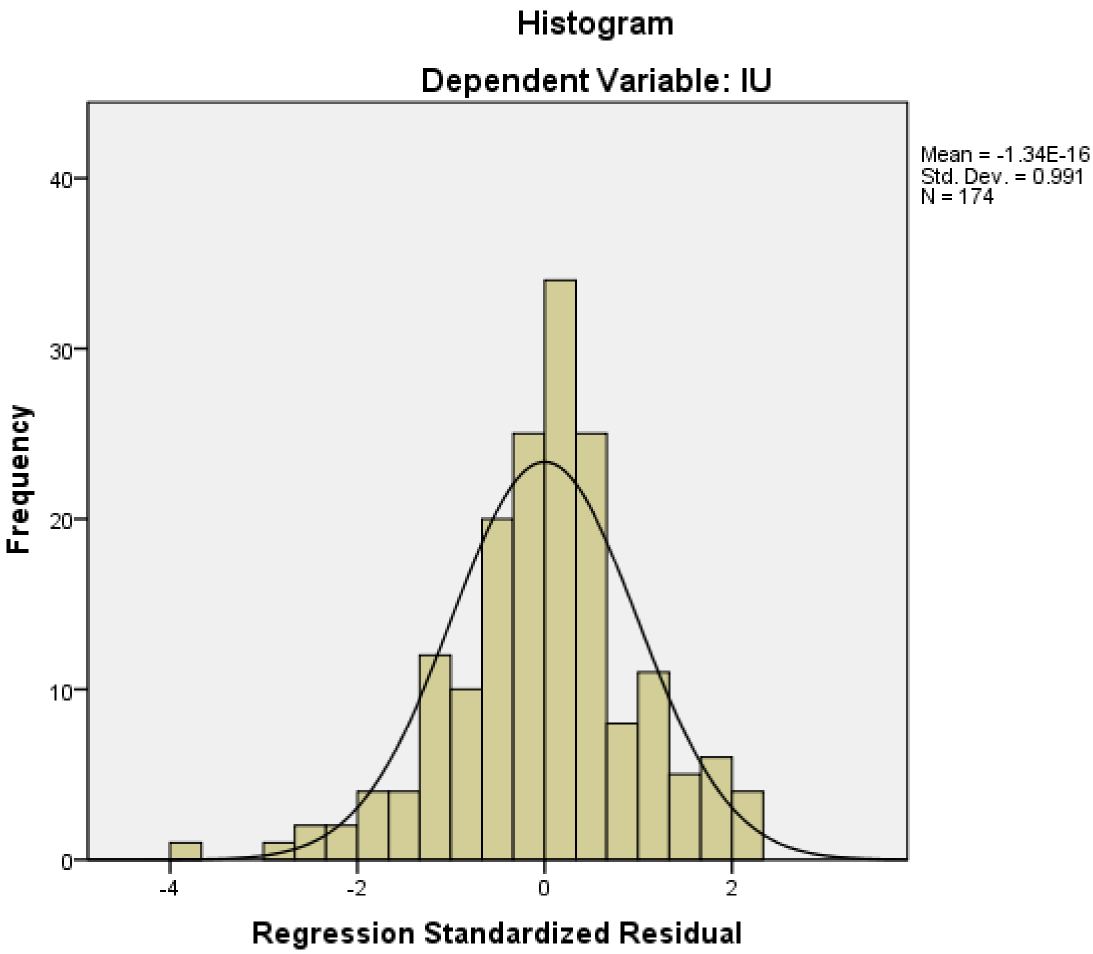


APPENDIX H – SCREE TEST CURVE

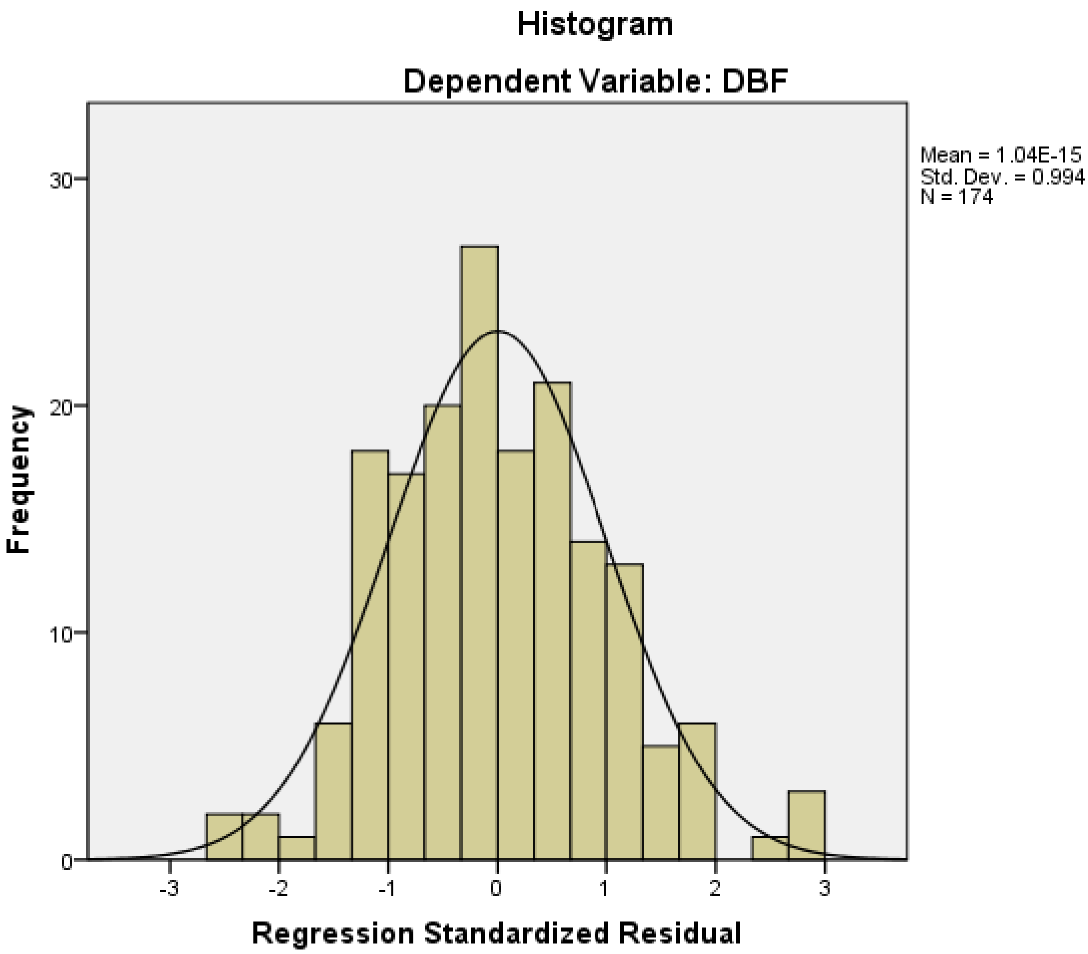


APPENDIX I – MULTIVARIATE NORMALITY (HISTOGRAMS)

Dependent variable IU

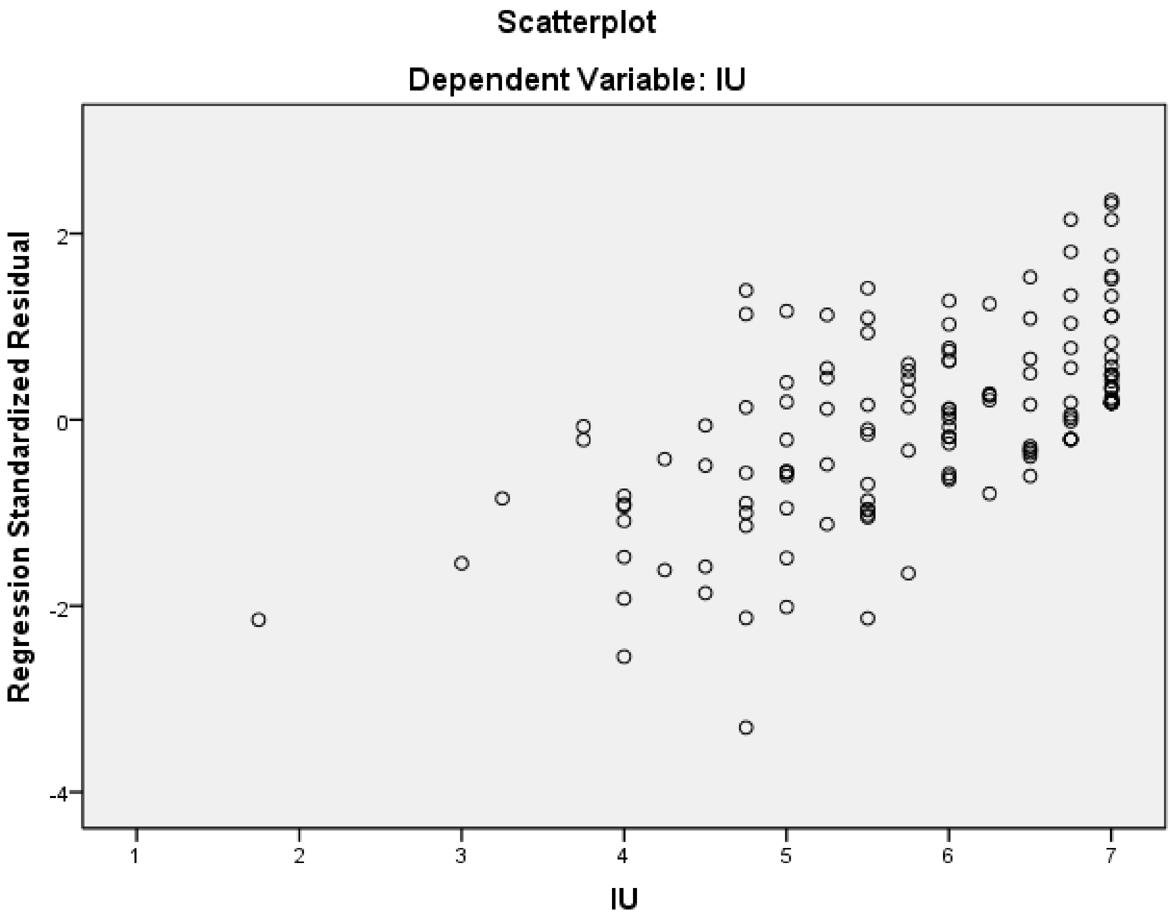


Dependent variable DBF



APPENDIX J - MULTIVARIATE SCATTERPLOTS

Dependent variable IU



Dependent variable PU