

A validation of the technology acceptance model on BI systems in a South African pharmaceutical organisation

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ABSTRACT

The aim of this study was to determine whether the relationship proposed by Technology Acceptance Model (TAM) that is, Behavioural intention to use (ITU) = Perceived Usefulness (PU) + Perceived Ease of Use (PEOU), remains valid when applied to Business Intelligence. More specifically applied to the MicroStrategy™ Business Intelligence tool in a South African Pharmaceutical organisation. This was done through firstly, a literature review of the Technology Acceptance Model, Business Intelligence and various related concepts. Secondly, a structured questionnaire served as the medium for empirical research.

The literature review highlighted prior research done on the Technology Acceptance Model, identifying the fundamental importance of the model to act as a starting point for user acceptance testing. Recent developments within the field of Business Intelligence were also discussed showing the need for more user involvement and the benefit of user acceptance testing.

The organisation used in this study had a respectable MicroStrategy™ user base with good potential for growth. MicroStrategy™ has proven to be a successful implementation within the organisation, offering a variety of solutions and services. A structured questionnaire was introduced to gather the necessary data. The data received from respondents was analysed to determine whether the Technology Acceptance Model could explain user acceptance in Business Intelligence. In order to do this a frequency analysis, descriptive statistics, reliability, internal consistency as well as correlations between constructs and questions were tested, discussed and compared to previous literature and research results.

Statistical significant correlations were found between all constructs and as depicted in literature, Perceived Usefulness had a much larger impact than Perceived Ease of Use on user acceptance. Linear regression was used to test the full impact of combined constructs. The results of the analysis were positive, with the model able to explain more than 50% of the variance in Intention to Use through the two constructs that is, Perceived Usefulness and Perceived Ease of Use.

KEY TERMS: Technology Acceptance Model, Behavioural intention to use, Attitude towards Using, Perceived Usefulness, Perceived Ease of Use, user acceptance, Business Intelligence, Information Systems, MicroStrategy

CHAPTER 1 ORIENTATION AND PROBLEM STATEMENT

1.1 INTRODUCTION

In today's corporate environment companies operate in a very complex, dynamic environment that require agility and proactive decision-making. To learn from the past and anticipate the future, many companies adopt Business Intelligence (BI) tools and systems (Marjanovic, 2007:215C). These Business Intelligence tools and systems enhance the speed and reliability of employees' decision-making ability to ultimately give the company a competitive advantage (Mikroyannidis & Theodoulidis, 2010:559).

Over the past decade, the Information Technology (IT) environment has changed. No longer do only upper management or certain departments reap the benefits of Business Intelligence; instead, it is more widespread and accessible throughout the company. Theoretically everyone in the organisation can now use Business Intelligence as a decision-making tool (Arvidsson & Pettersson, 2012:1). According to Watson and Wixom (2007:98) the key to successful Business Intelligence and a Business Intelligence-enabled business strategy is to integrate it at every level of the organisation. The use of information and analytics should form part of the organisational culture. To do this, all Business Intelligence users should accept and utilise systems to its full potential.

One of the most significant and validated theories used to study user acceptance of Information Systems (IS), is the Technology Acceptance Model (TAM) (King & He, 2006:740). This model suggests that system use, or more so, user acceptance is predicted by the user's motivation, which in turn is influenced by mainly two constructs:

1. Perceived Usefulness (PU); and
2. Perceived Ease of Use (PEOU) (Farahat, 2012:97).

In this study, the Technology Acceptance Model will be applied to Business Intelligence in the South African pharmaceutical environment; in order to determine whether it holds its legitimacy in determining user acceptance. This will be done through a literature review of Business Intelligence together with its underlying components as well as the pharmaceutical industry in terms of Business Intelligence. The Technology Acceptance Model will be empirically reviewed and discussed. Lastly, a survey will be used to validate the model with regards to parameters of the study.

1.2 CONTEXT

Business Intelligence has received increasing academic research although less extensive than the Technology Acceptance Model. Business Intelligence was conceptualised in the late 1958s but only truly took form in 2000 to 2007, when businesses started automating and integrating data for analytical decision-making reporting.

Today, Business Intelligence is a top priority among Chief Information Officers (CIO) and receives considerable attention and resources in numerous companies (Arvidsson & Pettersson, 2012:1; Yeoh & Koronios, 2010:23). Du Plessis (2012:1) provides a comprehensive definition of Business Intelligence stating that Business Intelligence is the process of getting enough of the right information at the right time to analyse it so that it can have a positive impact on business strategy, tactics or operations. Furthermore, Du Plessis (2012:49) differentiates between various Business Intelligence functions which include:

- Extract-Translate-Load (ETL);
- Activities of decision support;
- Query and reporting;
- Online Analytical Processing (OLAP);
- Statistical analysis;
- Forecasting;
- Data mining.

This research has been done on one particular Business Intelligence OLAP tool, MicroStrategy™.

The MicroStrategy™ Business Intelligence tool is quickly gaining popularity in the South African market, due to its impeccable analytical capabilities and its user-friendly development. The research has given new insight into the user acceptance of/and behaviour towards MicroStrategy™. The Technology Acceptance Model has been verified in its ability to assess and predict user acceptance. Previous studies have focused on general information systems (*for example* office automation software) and not so much on business process applications (Legris *et al.*, 2003:194).

An extensive literature search and the meta-analyses indicate that the Technology Acceptance Model has been applied to a business Intelligence reporting system, Qlickview, in Europe but not on MicroStrategy™ or in a South African context (Arvidsson & Pettersson, 2012:11). It would, therefore, be valuable to investigate whether the Technology Acceptance Model holds true for the MicroStrategy™ Business Intelligence system. It would also be valuable to determine any reasons for similarities or differences in the results compared to other studies.

1.3 CAUSAL FACTORS

The causal factors for this study are illustrated in Figure 1-1 and discussed in detail.

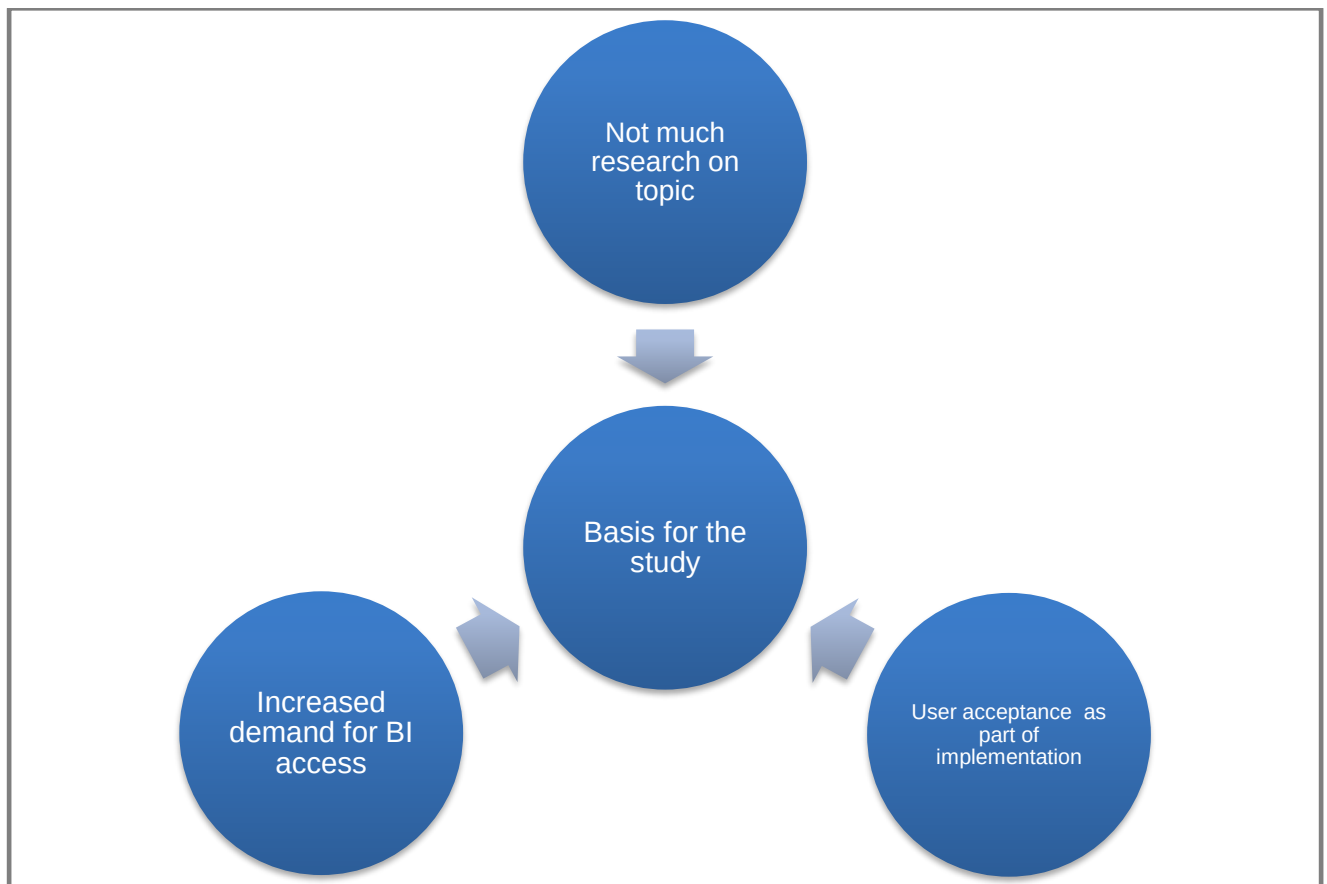


Figure 1-1: Basis for the study – Source: (Botha, 2012:4)

Limited research has been done to examine the user acceptance of Business Intelligence, particularly within the South African pharmaceutical environment. The Technology Acceptance Model has not been applied to Business Intelligence systems previously to any large extent. This provides a valuable opportunity to investigate whether the Technology Acceptance Model could be validated on Business Intelligence systems. An opportunity to explore any similarities or differences is also provided in the results, compared to other studies (Arvidsson & Pettersson, 2012:2).

Business Intelligence systems are constantly changing. On the one hand, it is driven by social media, smart devices and machine sensors generating new data and new data structures. On the other hand, the general scope of Business Intelligence has increased from the traditional strategic-question asked by management to operational tasks and querying system that almost all employees should use (Alpar & Schulz, 2016:151; Böhringer *et al.*, 2010:267). This increase in user base has taken strong effect on the South African pharmaceutical industry where a large

portion of the operational tasks are performed by product representatives, more commonly known as “reps”, sales and marketing teams. These reps, sales and marketing teams have increased the demand for real-time Business Intelligence data within their organisations. This need or even the implementation of a Business Intelligence system cannot improve organisational performance if the system is not utilised and more importantly utilised correctly (Olszak & Ziemba, 2012:134). For this reason, user acceptance has been identified as a key success factor for a successful information system implementation (Petter *et al.*, 2014:39).

1.4 IMPORTANCE OF THE STUDY

The study of Business Intelligence user acceptance in the South African pharmaceutical industry is foremost important due to the limited research available on this topic and specifically the geographical area. The general aim of this research is to validate the Technology Acceptance Model and to determine whether this comprehensive research model can be instrumental in predicting the level of commitment of end-users in accepting, using and exploiting the Business Intelligence tool MicroStrategy™.

This study has a management implication in the sense that the study and its results will serve as a key metric and benchmark for future implementations of Business Intelligence tools. The study also gives management insight into how to better manage the current acceptance levels and highlight focus areas for future implementation. The end result should allow management to increase the acceptance and adoption of the tool in order to increase productivity.

The target pharmaceutical organisation has an immense potential user-base but with a fairly moderate actual usage. This study will benefit the organisation by firstly, assisting management in understanding what the current levels of user acceptance and determining which factors contribute the most to the current situation. Secondly, with the insight gains from this study the organisation will be able to formulate focussed and informed change management strategies to improve user acceptance. Lastly, with this study and future studies like it, the organisation will be able to benchmark their user acceptance of Business Intelligence.

1.5 PROBLEM STATEMENT

Information Technology has become a key component in any 21st century business. For businesses to compete and survive, they are compelled to adopt new information technologies. One such technology highlighted by the Gartner's 2015 Hype Cycles report is Business Intelligence (Schlegel, 2015). This technology alone, however, cannot improve organisational

performance. Technology needs to be accepted, learned and optimally utilised for it to add value to the organisation. If new Information Technology is accepted and adopted by users, the chance of the system and investment being successful greatly increases (Arvidsson & Pettersson, 2012:7; Straub *et al.*, 1995:1328). One emerging technology trend is Business Intelligence and Business Intelligence tools. Little research has been done on Business Intelligence particularly about user acceptance in the South African pharmaceutical industry (Arvidsson & Pettersson, 2012:2).

The Technology Acceptance Model has gained popularity for its ability to assess and predict user acceptance. The model has yet to be applied on Business Intelligence and Business Intelligence tools; creating a unique opportunity to expand research on both Business Intelligence and the Technology Acceptance Model. User acceptance and the Technology Acceptance Model, in particular, has been well researched and verified over the last 30 years. Developed by Davis in the late 1986 and based on the Theory of Reasoned Action, the Technology Acceptance Model was specifically developed to explain user acceptance of information systems or technologies. Using the Theory of Reasoned Action as a theoretical basis, the Technology Acceptance Model is used to identify the causal links between Perceived Usefulness and Perceived Ease of Use, and among users' attitude, behavioural intention, and actual usage behaviour (Falaleeva & Johnson, 2002:1028-1033; Hou, 2014:585).

The model suggests that, when users encounter a new information system, there are two main factors which will influence how and when they will use it. These factors are (1) Perceived Usefulness and (2) Perceived Ease of Use (Falaleeva & Johnson, 2002; Hou, 2014:585).

Perceived usefulness is the degree to which an individual believes that using the particular information system or technology would increase their job performance. Perceived ease of use is the degree to which an individual believes that using a particular information system or technology effortless (Davis, 1986:26; Erasmus, 2014:3).

Although the Technology Acceptance Model has been developed further into a more elaborate model known as the Unified Theory of Acceptance and Use of Technology (UTAUT), it is also known as the TAM2 which is the original Technology Acceptance Model that still holds credit due to the validation and support it has received (Venkatesh & Davis, 2000:187). This study relies on the original Technology Acceptance Model proposed by Davis (1986:24) rather than the extended model of the UTAUT or TAM2 to measure technology acceptance.

1.6 RESEARCH OBJECTIVES

The research objectives of this study are divided into primary and secondary objectives and are discussed in Section 1.6.1 and 1.6.2 below:

1.6.1 Primary objectives

The general objective of this research is to validate the Technology Acceptance Model and to determine whether this comprehensive research model can be instrumental in predicting the level of commitment of Business Intelligence tools (MicroStrategy™) end users in accepting, using and exploiting the MicroStrategy™ system.

1.6.2 Secondary objectives

The specific objectives of this research are to:

- Validate the Technology Acceptance Model within the South African Pharmaceutical Business Intelligence user environment.
- Study the relationship between the Perceived Usefulness and Perceived Ease of Use, as well as their contribution towards Attitude towards Using and Behavioural intention to use.

1.7 RESEARCH METHODOLOGY

1.7.1 Literature and theoretical review

A literature and theoretical review on the areas of Business Intelligence, Business Intelligence tools, with specific attention to MicroStrategy™ was conducted. The Technology Acceptance Model and its measurements, namely:

- Perceived Usefulness;
- Perceived Ease of Use;
- Behavioural intention to use;
- Attitude towards Using.

1.7.2 Empirical research

To accomplish the research objectives of this study, empirical research was done among pharmaceutical organisations in South Africa. Primary data were collected in the form of results obtained through quantitative questionnaires sent out to the target group at the participating organisation. The questionnaires were formulated to receive independent responses from the individuals surveyed.

1.8 LAYOUT OF THE STUDY

The mini-dissertation is divided into five chapters, which are presented as follow:

CHAPTER 1 ORIENTATION AND PROBLEM STATEMENT

This chapter discusses the background, context of and causal factors of the study. The chapter will also depict the problem statement relating to the study and presents an overview of the research design.

CHAPTER 2 LITERATURE REVIEW

The literature review investigates the elements and function of Business Intelligence. It also reviews the importance of user acceptance and methods of measuring set acceptance, with specific attention given to the Technology Acceptance Model and its underlying elements.

CHAPTER 3 METHODOLOGY

This chapter presents the research methodology by discussing the sampling methods used as well as the compilation of the survey instrument, namely a questionnaire, the study participants and the data collection.

CHAPTER 4 RESULTS AND DISCUSSION

The results of the investigation will be presented and discussed in this chapter together with comparisons to previous results in related studies.

CHAPTER 5 CONCLUSION AND RECOMMENDATIONS

The conclusions of the study based on the literature review and empirical investigation, as well as recommendations for further study are presented in this final chapter.

1.9 CONCLUSION

In today's complex and fiercely competitive business environments, organisations need more real-time analysed data in order to make informed decisions and achieve a comparative advantage. In order to accomplish this, organisations are turning to Business Intelligence and spreading it across all facets of the organisation. This alone, however, will not ensure success. Employees need to use and adopt the system to reap its full benefit and ultimately contribute towards the organisations corporate strategy.

1.10 CHAPTER SUMMARY

The aim of this study is to determine whether the relationship proposed by Technology Acceptance Model that is, Behavioural intention to use = Perceived Usefulness + Perceived Ease of Use, remains valid when applied to Business Intelligence. More specifically applied to the MicroStrategy™ Business Intelligence tool in a South African Pharmaceutical organisation. This was done through firstly, a literature review of the Technology Acceptance Model, Business Intelligence and various related concepts. Secondly, a structured questionnaire will serve as the medium for empirical research.

This chapter introduces the study by emphasising the research problem, the need to address it and stated the objectives aimed at resolving the research problem. The chapter also provides a layout of the study and chapters to follow.

CHAPTER 2 LITERATURE REVIEW

2.1 INTRODUCTION

Information is everywhere; there is a continuous increase in both volume and detail of data captured by organisations. With the rise of social media and the internet of things organisations are producing overwhelming amounts of data, in either structured or unstructured format (Hashem *et al.*, 2015:99). Data creation is occurring at a record rate, and most organisations value this data as a strategic asset (Baltzan, 2015:6). Information Technology has become an essential component of doing business. For large organisations to stay ahead of competitors, it is vital that they analyse and learn from historical data to predict future outcomes (Marjanovic, 2007:215). One curtail technology implemented by organisations to manage and make sense of their data is Business Intelligence (BI) tools. These Business Intelligence tools and systems, store, transform, analyse and visually represent data; with the end goal of enhancing the speed and reliability of employees' decision-making ability to give organisations a competitive advantage (Mikroyannidis & Theodoulidis, 2010:559).

Business Intelligence technology like most technology needs to be accepted, learned and optimally utilised for it to add value to the organisation. If a new system is accepted and adopted by users, the chance of the system and investment being successful greatly increases (Arvidsson & Pettersson, 2012:7; Straub *et al.*, 1995:1328). To test whether users will accept and eventually use a particular system, various models can be applied which are designed to examine user behaviour and acceptance. One particular model that has been praised as one of the most important and well-researched models in this field is the Technology Acceptance Model (TAM) (Chuttur, 2009:9; Yousafzai *et al.*, 2007:251).

This chapter focuses on the Technology Acceptance Model and its constructs. The importance of the model in general and about Business Intelligence is emphasised. Business Intelligence and its supporting architecture are defined and discussed. A look into the future of Business Intelligence and the importance of user acceptance is also discussed.

2.2 USER ACCEPTANCE

The success of any Information Technology (IT) or system is mostly, if not completely, determined by user acceptance. The potential benefit an organisation stands to gain from a system be it increased productivity, performance, efficiency or any other positive outcome, will not matter if the users ultimately end up rejecting the system (Agarwal, 2000:86; Arvidsson & Pettersson,

2012:7). Thus, understanding the concept of acceptance and the drivers behind it is not only of academic interest but also of business value.

Developing and implementing a new system is often a strategic investment for an organisation that requires both internal change and a large financial commitment with an uncertain outcome (Amadi-Echendu & De Wit, 2015:210; Arvidsson & Pettersson, 2012:7). In this study, the concept of user acceptance refers to a user's predisposition toward using the system according to its purpose (Young Lee & Lehto, 2013:194). There are many ways to study user acceptance, but the most widely used model that specifically targets IT and IT systems is the Technology Acceptance Model (Arvidsson & Pettersson, 2012:7; Davis, 1986:24).

2.3 TECHNOLOGY ACCEPTANCE MODEL (TAM)

The Technology Acceptance Model is used to explain the acceptance of Information Technology and identify problems users might have interacting with the system. The Technology Acceptance Model is able to test this across a wide range of settings and applications while at the same time being theoretically well founded. This also enables an organisation to test whether users or a particular group of users have an intention to use a particular technology before large scale roll-outs (Arvidsson & Pettersson, 2012:7; Farahat, 2012:96).

The Technology Acceptance Model is one of the most important, used and tested theories studying user acceptance of information systems (Yousafzai *et al.*, 2007:251). This model also gained considerable support over the cores of more than a decade, in understanding and managing the process of new technology adoption (Farahat, 2012:96; Park, 2009:151). The model has been recognised as one of the most powerful models to define user acceptance of Information Technology. It has been both commended and criticised for its avid nature and simplicity (Chuttur, 2009:9). In short, the model proposes that user acceptance is predicted by user-motivation, which is influenced by mainly two concepts: (1) Perceived Usefulness (PU) and (2) Perceived Ease of Use (PEOU) (Arvidsson & Pettersson, 2012:2).

The Technology Acceptance Model was developed as an adaptation of the Theory of Reasoned Action (TRA). The TRA, illustrated in Figure 2-1, was proposed to explain and predict the behaviour of people in a specific situation (Chuttur, 2009:12). The Technology Acceptance Model builds on the TRA and attempts to address why users accept or reject Information Technology (Park, 2009:151).

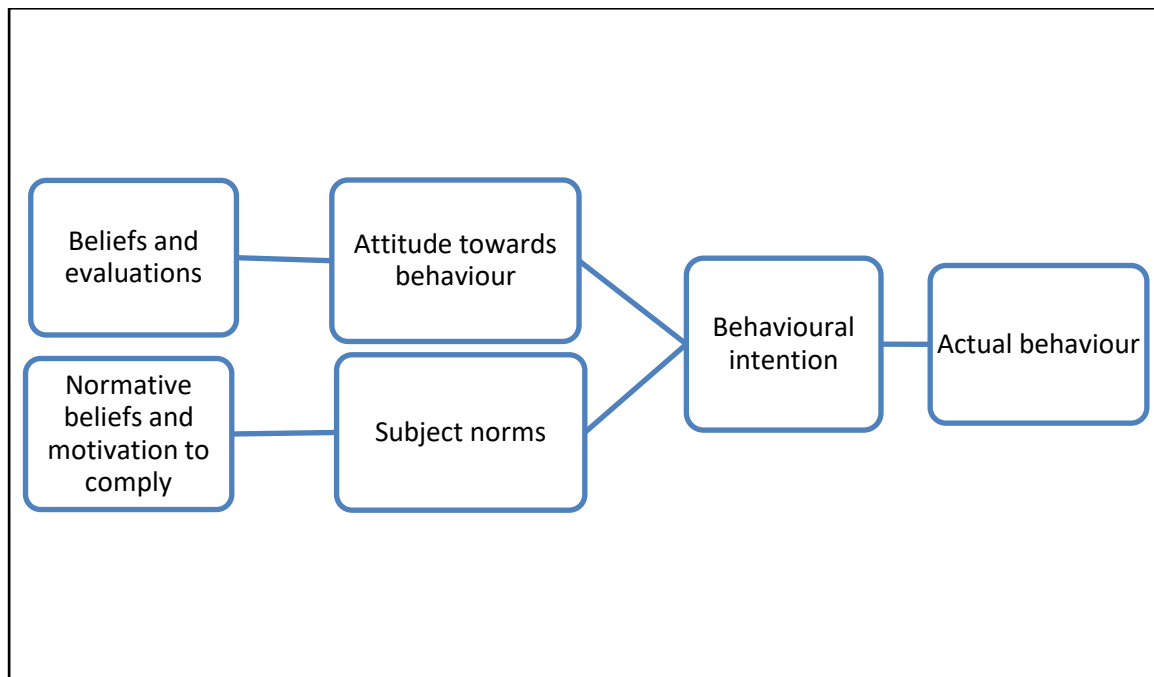


Figure 2-1: Theory of Reasoned Action. Source: (Chuttur, 2009:12)

The Technology Acceptance Model suggests that users formulate a positive attitude toward technology when they perceive it to be useful and easy to use. The model describes the relationship between these two main constructs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as positive and theorised that they are fundamental determinants of user acceptance. PU and PEOU capture and mediate the effects of other external variables on system use, as can be seen in Figure 2-2 (Farahat, 2012:97).

External variables intervene indirectly, influencing attitude, subject norms or PU and PEOU. Attitude toward Using (ATU) and behavioural intent are subject norms in the Technology Acceptance Model (Legris *et al.*, 2003:192). Thus one's actual use of a technology system is influenced directly or indirectly by the user's behavioural intentions, attitude, Perceived Usefulness of the system, and Perceived Ease to Use the system (Park, 2009:151).

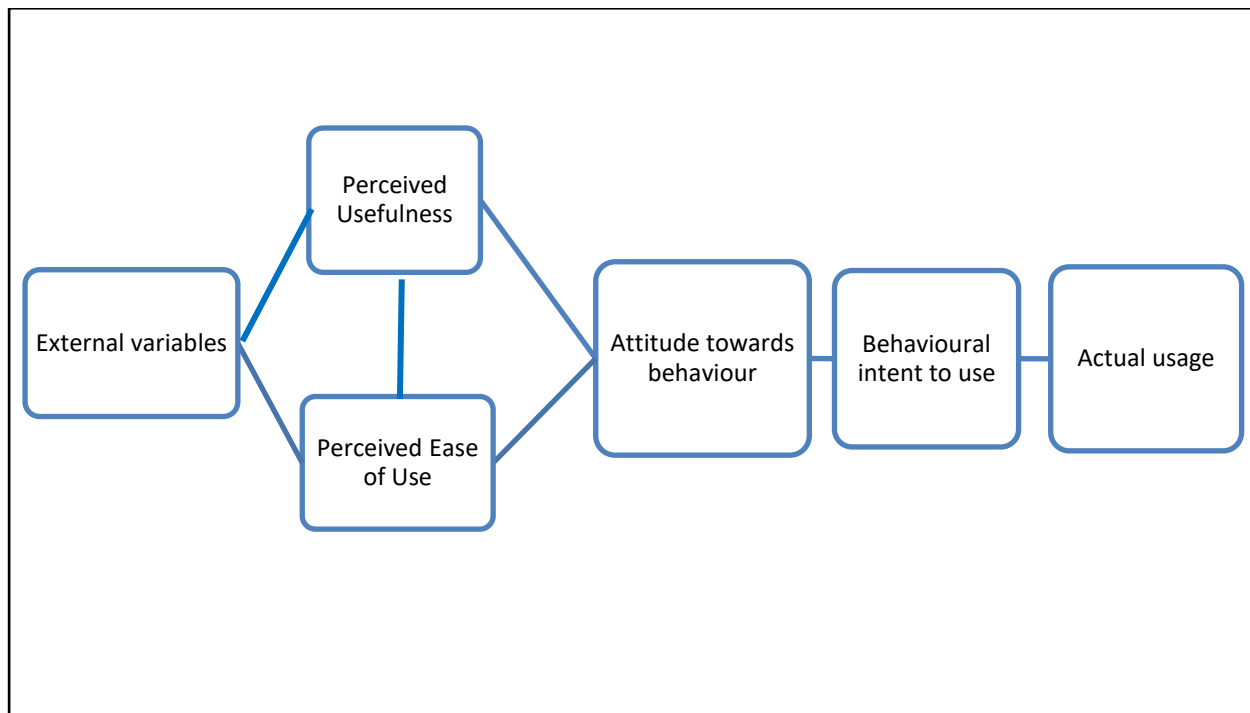


Figure 2-2: Technology Acceptance Model. Source: (Farahat, 2012:97; Park, 2009:151)

Liao *et al.* (2009:310) defined Perceived Usefulness (PU) as “the degree to which a person believes that using a particular system would enhance his or her job performance”, furthermore he defined Perceived Ease of Use (PEOU) as “the degree to which a person believes that using a particular system would be free of effort”.

The actual system use is determined by a person’s behavioural intention, which mediates PU and PEOU (Arvidsson & Pettersson, 2012:7). Research shows that the Perceived Ease of Use of technology may have a direct effect on the Perceived Usefulness of the corresponding information system. However, the reverse is not true, meaning that technology that is perceived as useful may not necessarily be easy to use (Amadi-Echendu & De Wit, 2015:210). This makes sense conceptually. If a system is not useful to a particular user, it does not matter how easy it is to use. If it is useful to that user, however, then he/she can learn to live with the hardship of a more difficult to use the system. Thus, the more useful a user perceives a system to be, the more the user will use it. If a system is easy to use, it also affects usage positively but to a lesser extent than Perceived Usefulness. If a system is easy to use, it can make the system appear more useful in the eyes of the beholder (Arvidsson & Pettersson, 2012:8).

Numerous studies have been conducted to verify the Technology Acceptance Model using diverse empirical data and in various application contexts (Liao *et al.*, 2009:309-310). Most research results portray the Technology Acceptance Model to be a valid and robust model that has been widely used but which also has potentially wider applicability (King & He, 2006:740).

Several other theories such as self-efficacy theory, the cost-benefit paradigm and research on the adoption of innovations, has supported the theoretical foundations of the model (Farahat, 2012:96). A meta-analysis of 88 Technology Acceptance Model studies involving more than 12,000 observations provided powerful large-sample evidence that the Technology Acceptance Model measures (PU, PEOU and behavioural intent) are highly reliable and may be used in a variety of contexts (King & He, 2006:751). However, not all research on Technology Acceptance Model has been conclusive. Arvidsson and Pettersson (2012:8) noted that several studies have not been able to find a significant relationship between PEOU and system use. According to Legris *et al.* (2003:159) the results of Technology Acceptance Model studies have not been totally consistent nor have they always been clear. Other researchers have criticised methodological and theoretical assumptions that, according to them, were flawed (Farahat, 2012:97; Kim *et al.*, 2009:69).

The Technology Acceptance Model has received much attention over the last decade. This has led to many researchers updated or modifying the model in an attempt to empirically verify particular assumptions (Farahat, 2012:97). For instance, Viswanath and Davis (1996:455) dropped the attitude construct from the original model. They theorised that it does not entirely mediate the relationship between the main constructs (that is, Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) and behavioural intent) (Kim *et al.*, 2009:69). Similarly, other researchers dropped actual use or the external variables constructs from the model (Masrom, 2007:3). On the other hand, Lee *et al.* (2005:1096) included perceived enjoyment as an intrinsic motivator into Technology Acceptance Model to examine the impact of perceived enjoyment on both users' attitude and intention to use internet-based learning systems. Other additions made to the Technology Acceptance Model include:

- Perceived behavioural control;
- Long and short-term usefulness;
- Anticipated perceived ease of use-system;
- Perceived developer responsiveness;
- Impact of adequate training;
- Additions of various subject norms;
- Combining the TAM with the Theory of Planned Behaviour (TPB) or the Theory of Reasoned Action (TRA) models (Legris *et al.*, 2003:194).

Even though the Technology Acceptance Model has received criticism and been modified and elaborated upon over the years, the Technology Acceptance Model still compares favourably to alternative or competing models on the user acceptance front. Most user acceptance studies use the Technology Acceptance Model as a starting point for their research.

This further validates the importance of the model as the Technology Acceptance Model provided a starting point for user acceptance research and opens up the field for extensions and elaborations (Lee *et al.*, 2003:765).

2.3.1 Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

Perceived Usefulness, as defined previously, is the extent to which a user trusts that using a particular technology will produce better outcomes (Davis, 1986:26; Young Lee & Lehto, 2013:194). Thus, if a user perceives that the system can help improve their performance, they will be more likely to use the system (Farahat, 2012:96-97). Perceived Ease of Use refers to a user's perception and the extent thereof that using a particular system would be free of effort (Davis, 1986:26; Young Lee & Lehto, 2013:194).

Thus, the user's perception of the amount of effort required to utilise the system or the extent to which a user believes that using a particular technology will be effortless. These two individual beliefs mediate the influence on user acceptance arising from other external variables (Arvidsson & Pettersson, 2012:2; Farahat, 2012:97; Zhang & Mao, 2008:790).

2.3.2 Behavioural Intent and Actual Usage

The core idea of the Technology Acceptance Model is that a user's acceptance of technology is determined by the user's behavioural intention, which in turn is determined by PU and PEOU. Behavioural intention is used to express the extent to which a user formulates conscious plans to use or not to use a system (Liu *et al.*, 2009:601). Behavioural intention is strongly related to the person's actual behaviour; in other words, if a person intends to behave in a particular manner, it is likely to be done (Farahat, 2012:97). The actual usage of the system is therefore strongly influenced by this behavioural intent, which is ultimately influenced by PU and PEOU (Farahat, 2012:96).

2.4 USER SATISFACTION

User satisfaction is defined as the degree to which enjoyment and gratification are experienced by a person using a particular information system (Capece & Campisi, 2013:336). Throughout user satisfaction literature system and information design attributes, for example, information accuracy and system reliability are acknowledged as primary contributors to user satisfaction. This potentially allows for valuable diagnostics for system design but not in a predictor of system

use. This is ascribed to the fact that beliefs and attitudes about information system are poor predictors of behaviours, such as system usage (Wixom & Todd, 2005:85).

Furthermore, Wixom and Todd (2005:85) state that, in contrast to user satisfaction models, the Technology Acceptance Model provides sound and proven predictions of usage by linking behaviours to attitudes and beliefs.

One of the most important and long-standing research questions in information system literature is how to truthfully explain user acceptance of information systems. The leading model in this area of research and the basis for many other studies is the Technology Acceptance Model that is used to explain user acceptance (Van Der Heijden, 2004:695).

2.5 INFORMATION SYSTEMS

Information systems enable organisations to improve their business processes and operations, as well as to provide better products and services. Computerised information systems are characteristically implemented and utilised in business operations to facilitate reporting and enhance decision-making capability (Amadi-Echendu & De Wit, 2015:209).

Over the years, information system usage and acceptance have been an imperative focus of information system research. Researchers have sought to establish a theoretical framework by explaining the determinants and mechanisms of users' adoption decisions. Liao *et al.* (2009:309) stated that the adoption process influences the successful use of information systems. The Technology Acceptance Model originally developed by Davis (1986:24) has dominated information system "use" research which resulted in an in-depth examination and extensive debates over its application and additions. The core focus of the Technology Acceptance Model is the initial acceptance of information systems. It theorises that system use is directly determined by Behavioural intention to use which in turn motivates the user's attitude towards system use (Liao *et al.*, 2009:309).

2.6 BUSINESS INTELLIGENCE (BI)

Business Intelligence is a subject that has seen extensive discussions throughout literature. The interest in the subject has increased considerably over the last decade since opinions began to surface suggesting that Business Intelligence is a crucial component of a modern organisation's Information Technology infrastructure, as it contributes to organisational success and competitiveness (Olszak & Ziemba, 2012:129).

Business Intelligence applications have been dominating the technology priority list of many Chief Information Officers (CIO) as organisations attempt to derive value from their data, and more recently, Big Data initiatives (Yeoh & Koronios, 2010:23). In general terms, Business Intelligence is turning data into information and knowledge through the use of Information Technology that can be used by all levels of the organisation in the decision-making process (Sparks & McCann, 2015:31-32).

The term of Business Intelligence has been defined in different ways, and there is no universally accepted definition of Business Intelligence. Most believe that the term Business Intelligence was first used as a common name for describing the concept of improving business decisions through the practise using information and facts from supporting systems (Olszak & Ziemia, 2012:130).

In this study, we will refer to Business Intelligence as specific practices, tools and technologies used to combine data gathering, data storage and knowledge management with analytical tools to present complex internal and competitive information to planners and decision makers (Du Plessis, 2012:1-2; Lloyd, 2011:34). Arvidsson and Pettersson (2012:4) define the purpose of Business Intelligence as, to deliver the right (accurate) information at the right time, at the right location and in the right form to support decision makers. It is important to note that the Business Intelligence concept is not just a technological tool or system; it is a managerial philosophy used to assist organisations in managing and refining business-information with the objective of making more informed business decisions throughout the organisation (Arvidsson & Pettersson, 2012:4; Lloyd, 2011:11).

At senior management levels, Business Intelligence provides the input to strategic and tactical decisions. At middle and lower managerial levels, it assists individuals to do their day-to-day job (operational). On a strategic level, Business Intelligence provides predictive analytical and forecasting data used to predict future results based on historical data. On a tactical level Business Intelligence provides a basis for decision-making to optimise actions for overall company performance; and on an operational level, Business Intelligence provide real-time and accurate analysis of departmental performance. Thus Business Intelligence can be used to guide and improve decision-making at all levels, strategic, tactical and operational (Lloyd, 2011:13).

Simply put, the core purpose of Business Intelligence is the intelligent exploration, integration, aggregation and a multidimensional analysis of data originating from various information resources with an end goal of improving the organisation and its decision-making capability (Yeoh & Koronios, 2010:23). Throughout literature there are many different yet similar definitions for Business Intelligence; Arvidsson and Pettersson (2012:4) noted that a constant problem with Business Intelligence definitions is that most do not incorporate any human aspect in the Business Intelligence process. Instead, most definitions focus mainly on the technical aspect such as

system architecture and software. Arvidsson and Pettersson (2012:4) emphasises that Business Intelligence is nothing without the people (users) that interpret the meaning of the information provided and make informed decisions based on this information.

Business Intelligence systems may be analysed from two perspectives namely, business and technical: From the business perspective, Business Intelligence refers to a specific philosophy and methodology that the organisation follows when it comes to information and knowledge, open communication, information sharing and an analytic approach to business processes within the organisation. Business Intelligence solutions are responsible for the transformation of data into information and knowledge, and they should generate an atmosphere for effective decision-making and strategic thinking within the organisation (Olszak & Ziemia, 2012:131-132).

From a technical perspective, Business Intelligence is an integrated set of tools, technologies and software products that are used to gather heterogenic data from various scattered sources and then integrate and analyse the data to make it commonly available (Lloyd, 2011:11). To do this, Business Intelligence architecture is developed to manage the data flow and seamlessly interlink the various components.

2.6.1 Business Intelligence Architecture

A Business Intelligence system needs to incorporate two primary activities: (1) getting data in and (2) getting data out (Watson & Wixom, 2007:96). Various integrated processes separate these two activities, such as: data that is collected, managed, analysed and reported (Arvidsson & Pettersson, 2012:4).

Today's Business Intelligence architecture typically comprises of a data warehouse, which consolidates data from several operational databases. This data warehouse services a variety of front-end querying, reporting, and analytic tools. The back-end of the architecture is a data integration channel for populating the data warehouse by extracting data from dispersed and heterogeneous sources; cleaning, integrating and transforming data before loading it into the data warehouse (Lloyd, 2011:34).

The data warehouse is a key technology used to build Business Intelligence systems. Olszak and Ziemia, (2012:131) state that the main tasks faced by Business Intelligence systems include intelligent exploration, integration, aggregation, and a multidimensional analysis of data originating from various information resources. These Business Intelligence tasks in totality are performed using key tools and applications throughout the Business Intelligence process forming the Business Intelligence architecture. Figure 2-3 illustrates the core tasks performed at each

point within the architecture; Sections 2.6.1.1 to 2.6.1.5 provide a discussion of tools and key inflection points throughout the data flow process.

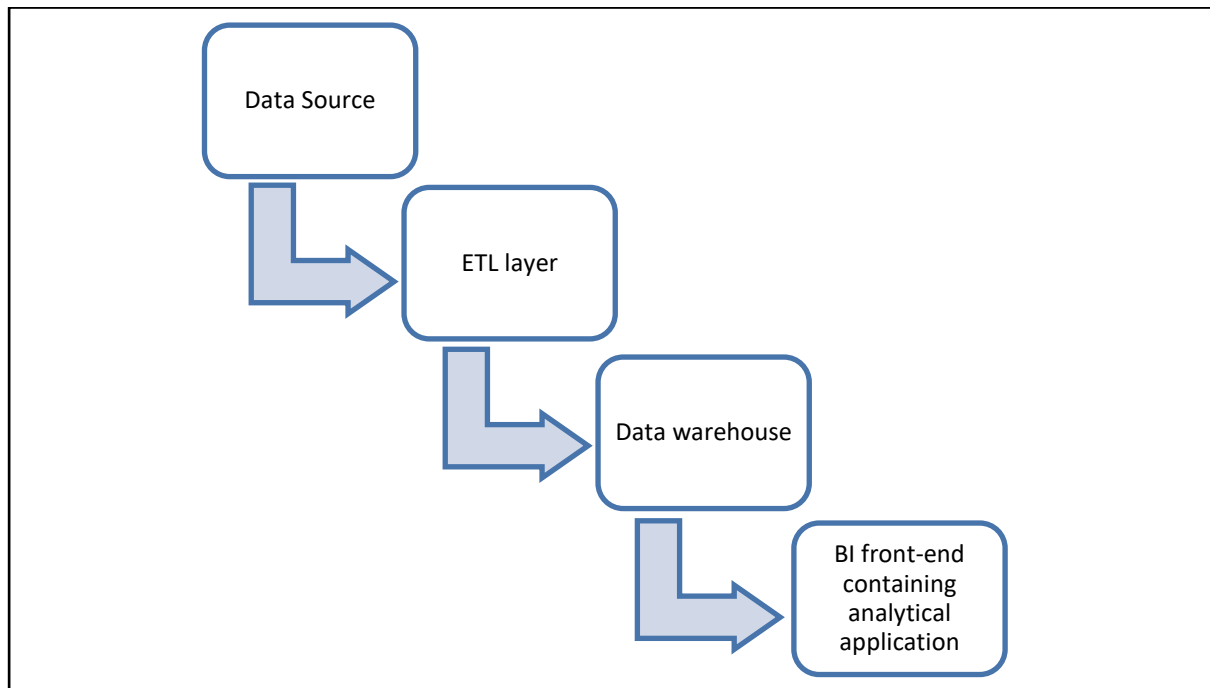


Figure 2-3: Business Intelligence data flow. Source: (Wu *et al.*, 2007:283)

2.6.1.1 Extraction-Transformation-Load (ETL) tools

ETL tools are used for data transfer from transaction systems, the internet or other data sources into data warehouses or data repositories (Olszak & Ziemba, 2012:131). Data is cleaned and transformed into a decision-ready state that conforms to universal business rules set up by the organisation. Data must also be standardised so that particular business concepts are transparent and have the same meaning to everyone in the company (Arvidsson & Pettersson, 2012:5).

2.6.1.2 Data warehouses and data repositories

A data warehouse is a subject oriented, collection of data stored in an aggregated and already to be analysed format. The metadata repository (usually also stored on the data warehouse) contains “data about the data”, which entails the definitions of the data and how it should be used (Arvidsson & Pettersson, 2012:5; Lloyd, 2011:19).

2.6.1.3 Analytic tools such as On-Line Analytical Processing (OLAP)

OLAP applications enable users to access, analyse, model business problems and share information that is stored in data warehouses (Olszak & Ziemba, 2012:131). This is done through further aggregating large volumes of data in a cube which can be accessed by users in a user- friendly manner (Arvidsson & Pettersson, 2012:5; Lloyd, 2011:20). Some of the most widely used OLAP tools today include:

- MicroStrategy™;
- Qlickview;
- IBM Cognos;
- Microsoft Business Intelligence platform;
- Oracle Business Intelligence;
- SAP Business Intelligence;
- SAS Business Intelligence;
- Tablo;
- YeallowFin;
- Clear Analytics (Baiju, 2014).

2.6.1.4 Data mining tools

Incorporates advanced statistical techniques at an attempt to discover and identify various patterns, relationships, generalisations and rules between variables and data sources (Arvidsson & Pettersson, 2012:5; Olszak & Ziemba, 2012:131).

2.6.1.5 Reporting and presentation tools

These tools allow users to interact with the data in an easy manner. It allows users create ad-hoc reports and queries. It also allows them to create visualisations of complex data and to collaborate and share data with others (Arvidsson & Pettersson, 2012:5).

Historically Business Intelligence systems have been used primarily for off-line, strategic decision-making. Performing one-way data integration through batch process, usually implemented by extract-transform load (ETL) tools. More recently however increasingly, as enterprises become more automated, data driven, and real-time, the Business Intelligence architecture is evolving to support operational decision-making (Lloyd, 2011:34). This demands additional requirements, resulting in more complexity in the design of data integration flows. These include reducing the latency so that near real-time data can be delivered to the data warehouse, extracting information

from a wider variety of data sources, exposing the ETL processes to new data sources and more unstructured data formats, as well as the phenomenon of Big Data (Böhringer *et al.*, 2010:268).

Big Data is a broad term used to describe data sets that are large, complex, and cannot be addressed by traditional IT methodologies and applications (Larson & Chang, 2016:701). Traditional data processing has changed due to how data is generated today. Historically IT departments managed transaction processing systems. Data captured was predominantly transactional, for example, orders, sales, shipments, inventory, and accounting. Transactional data is stable, structured and well understood by the organisation.

The core difference between transactional data and Big Data is volume, variety, velocity and veracity (Abbasi *et al.*, 2016:4). Volume refers to the amount of data, variety is based on the types of data sources, velocity represents the age of data and veracity refers to the credibility of data (Abbasi *et al.*, 2016:4; Larson & Chang, 2016:701). Volumes for Big Data is measured more than 100 TB or petabytes (although research in this threshold varies), compared to transactional data which is usually tens of terabytes or less (Larson & Chang, 2016:701). Big Data is also characterised by data types considered unstructured – not predefined or known – thus a high degree of variety and sometimes low credibility (Abbasi *et al.*, 2016:5). In contrast to transactional data which focuses on “what has happened”, Big Data is used in machine learning and predictive analytics where organisations focus on “what will happen” (Larson & Chang, 2016:701).

With additional data, come additional requirements from business users and vice versa. The introduction of Big Data and predictive analytics, the role of Business Intelligence systems and their influence on organisations have been subject to large-scale change. From simple, static analytical applications they have evolved into solutions that can be used in strategic planning, customer relationship management, monitoring operations, predicting the profitability and market impact (Olszak & Ziemba, 2012:130).

In recent years, Business Intelligence systems have undergone fundamental changes. On the one hand, social media systems, machine sensors, devices like smartphones, and other sources generate new and to an extent Big Data which differs from traditional operational data. On the other hand, the scope of Business Intelligence has dramatically increased from strategic questions to a combination of operational tasks and predictive analytic, requiring more employees have access to Business Intelligence data.

These developments have increased the demand as well as the frequency for Business Intelligence reporting. Consequently, Business Intelligence specialists who are either IT professionals or experienced Business Intelligence users in functional departments (so-called power users) has become an even bigger bottleneck than before.

To combat this phenomenon most, OLAP tools include a component offering self-service Business Intelligence (Alpar & Schulz, 2016:151).

2.6.2 Business Intelligence for the Masses and Self-Service Business Intelligence

“Self-Service Business Intelligence”, “Pervasive Business Intelligence”, or “Business Intelligence for the masses” has come to be known as the term for providing Business Intelligence to a broad mass of people within the organisation. Nevertheless, all of these terms encompass the idea of spreading the use of Business Intelligence throughout the organisation. With the aim of making Business Intelligence use more self-sufficient and delegating the task of application creation and maintenance from the IT department towards empowered end-users (Arvidsson & Pettersson, 2012:6). The user empowerment provided by self-service Business Intelligence can, however, only be achieved if user acceptance is achieved and employees actively use the system to better their job performance (Arvidsson & Pettersson, 2012:8).

Self-service Business Intelligence highlights flexibility by joining new data sources, increasing the speed of report development and introducing new data warehouse methods (Johansson *et al.*, 2015:49; Kisielnicki & Misiak, 2016:164). Introducing a self-service functionality to a Business Intelligence environment requires both extensive user involvement as well as system support. A self-service concept can be implemented on different tasks: access to prepared reports or data resources, direct access to data, access to functions, or creation of new resources. The system supports necessary varieties with each of these tasks as shown in Figure 2-4 (Alpar & Schulz, 2016:152).

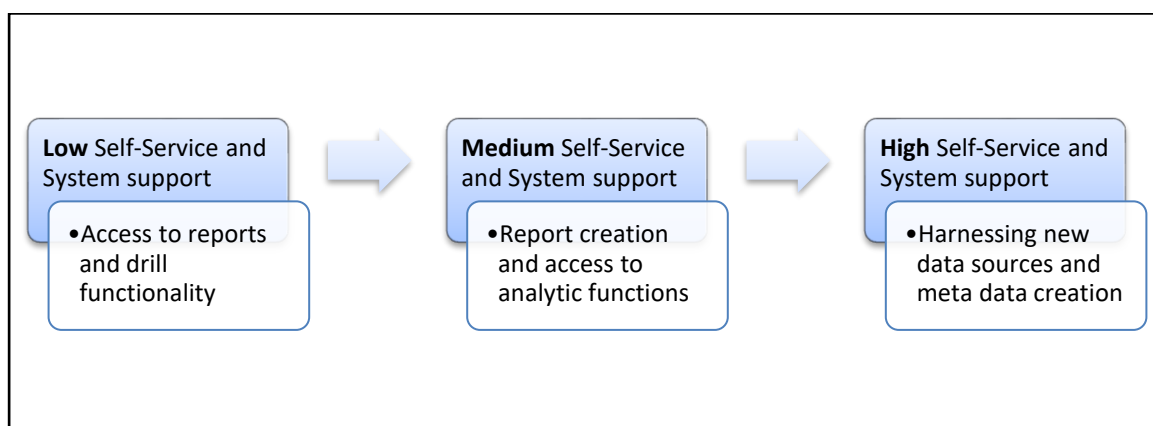


Figure 2-4: Self-service levels and system support. Source: (Alpar & Schulz, 2016:152)

The traditional adoption rates for Business Intelligence usage has been relatively low, primarily because they have been highly reliant on IT staff, analysts, and power users for their information (Miller *et al.*, 2016:759). The successful implementation of OLAP tools is heavily reliant on user engagement and adoption by users (Miller *et al.*, 2016:758).

Traditional Business Intelligence focused primarily on the limited scope of simply collecting and presenting data, and as such, these applications have an estimated user adoption rate of 3% to 8%. One reason for this low user adoption rate is because traditional Business Intelligence applications are too complex for business users (Miller *et al.*, 2016:759). Current Business Intelligence tools still have a fairly low adoption rate of 22% but according to a study done by Miller *et al.* (2016:759), with appropriate budgets, clean data, and organisational policies that support Business Intelligence the potential user adoption is 50% of employees.

With Chief Information Officers (CIO) indicated that Business Intelligence and analytics are at the top of their priority lists. Business Intelligence continues to be a major strategic focus for many organisations and with the continuous expansion and disruption of Big Data, this priority is getting attention from all departments within (Sparks & McCann, 2015:32).

2.7 CONCLUSION

Even though the Technology Acceptance Model has its flaws according to some critics, it is still a highly accepted, established and widely used model within information system research concerning technology acceptance and usage. Throughout the literature review there was little evidence that the original Technology Acceptance Model has been applied to Business Intelligence self-service tools nor has it been applied on any Business Intelligence platform in a South African pharmaceutical context.

With the Business Intelligence environment constantly changing and requiring more user involvement the Technology Acceptance Model is a good point of departure for investigating user behaviour. Extensions to the Technology Acceptance Model for example, TAM2, UTAUT, have not nearly been researched as much as the original model, and as stated by (Lee *et al.*, 2003:765) the Technology Acceptance Model serves as a starting point for technology acceptance research.

2.8 CHAPTER SUMMARY

In this chapter, various concepts relating user acceptance of information systems were firstly, defined. Secondly, the Technology Acceptance Model and its constructs were discussed, along with Business Intelligence and its business and technical aspects. Thirdly, the literature highlighted prior research done on the Technology Acceptance Model, identifying the fundamental importance of the model to act as a starting point for user acceptance testing. Lastly, the recent developments within the field of Business Intelligence were discussed showing the need for more user involvement and the benefit of user acceptance testing.

CHAPTER 3 METHODOLOGY

3.1 INTRODUCTION

The literature review done in Chapter 2 provided an overview of Business Intelligence (BI) and its transition to a more user involved, “Business Intelligence for the masses” approach. The chapter also highlighted the need for users to accept the system. In order to test user acceptance of Business Intelligence, an acceptance model must be tested on users, both current and prospected users.

Throughout the literature review, little evidence was found of research combining technology acceptance and Business Intelligence. As Lee, *et al.* (2003:765) highlights, the Technology Acceptance Model (TAM) should be a starting point for user acceptance research. Thus the original Technology Acceptance Model was tested on a Business Intelligence system to determine whether the relationships presented in the model, that is, Behavioural intention to use = Perceived Usefulness + Perceived Ease of Use, holds true.

This chapter presents the research methodology followed during the research. The discussion includes the research setting, describing the details of both the population and the specific Business Intelligence tool used in the study. The research strategy and design, as well as the measures and data processing, are discussed.

3.2 RESEARCH SETTING

A large South African pharmaceutical manufacturer was used for the basis of the study. The organisation implemented a self-service Business Intelligence system in 2012 called MicroStrategy™, which provided a sustainable yet fast growing user base. The user base consists of 230 online user accounts, actively accessing the self-service On-Line Analytical Processing (OLAP) services and over 150 distribution accounts (receiving push-reports without logging on). In keeping up with Business Intelligence’ evolution, the organisation strives to get all users to use the self-service function. The organisation has a total of 2,374 employees and presents a good opportunity to grow its Business Intelligence user base.

MicroStrategy™ is a Business Intelligence tool that aims to provide the most flexible, powerful, scalable, user-friendly analytics and identity management platforms, offered either on premises or in the cloud (MicroStrategy™, 2016a). MicroStrategy™ combines self-service data preparation, visual data discovery and Big Data exploration with enterprise business intelligence.

It is well-suited to organisations that require large-scale system-of-record reporting, mobile, dashboards and robust business-oriented data discovery on large complex datasets in a single platform. Through MicroStrategy™ in-memory engine, it allows greater scale and performance on large deployments across relational and Hadoop data sources resulting in fast interactive visualisation of large datasets.

MicroStrategy™ is an early innovator in mobile Business Intelligence with one of the most comprehensive, highly rated and widely adopted mobile capabilities (Gartner, 2016:31-32). Customers choose MicroStrategy™ for mobile more often than most other vendors. MicroStrategy™ Mobile is a fully-featured and native mobile development and consumption environment for iOS, Android and BlackBerry (BIScorecard, 2014:23). It supports advanced and less-common features such as disconnected analysis, write-back, GPS and camera integration, although authoring from a mobile device is not supported (Figure 3-1).

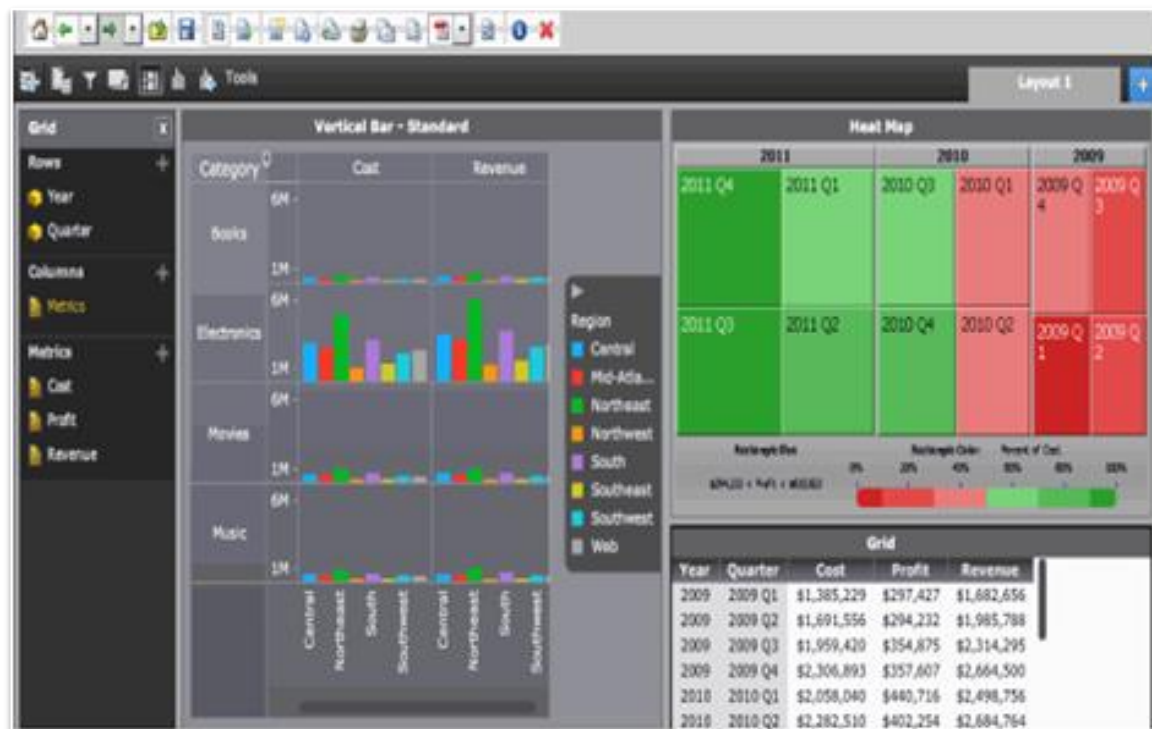


Figure 3-1: MicroStrategy™ Interactive OLAP dashboard illustrating heatmap and grid-graph functionality. Source: (MicroStrategy Incorporated, 2016b)

MicroStrategy™ offers a user-friendly web interface that users access through the organisation's internal web portal. Users have the ability to run or create reports, dashboards, visualisations, analyses and ad hoc queries. Users can also share their creations with other employees or subscribe to receive updated versions. The case organisation has a comprehensive data warehouse serving the Business Intelligence tool, allowing for rich data in all aspects of the

organisations (Figure 3-2). These include: sales, orders, procurement, manufacturing, distribution, customer service, and more.



Figure 3-2: MicroStrategy™ Dashboard document illustrating key performance measures on various flash graphs and-widgets. Source: (MicroStrategy™ Incorporated, 2016b).

In summary MicroStrategy™ is classified as a self-service Business Intelligence system with a focus on the end-user analytic capability. MicroStrategy™ is the case system in this study as it represents a progression towards Business Intelligence for the masses. The system has also been used for a considerable amount of time by the organisation in question, offering a well-known system with large user-base growth potential. Thus, enabling the possibility of studying acceptance across a broad mass of people.

3.3 RESEARCH STRATEGY AND DESIGN

A quantitative research methodology was followed in this study, in order to test the relationship proposed by the model and the phenomena of user acceptance, through the collection of abundant numerical data. Opposed to qualitative research which would have been more subjective and not necessarily represents the sentiment of the majority population.

The research approach adopted in this study was that of a structured questionnaire. This approach was selected for the following reasons:

- The aim of this study is to investigate user perception of a particular system and how the perception translates into system use. The purpose is therefore to test an attitude, which according to Welman *et al.* (2010:152) a survey strategy is often the most suitable. Particularly if a model is to be tested where its variables are correlated to each other.
- A fairly large sample of data was required to properly test the model and draw significant conclusions. Thus, interviews or observation was not deemed feasible.
- Most prior research on the Technology Acceptance Model was done through questionnaires (Arvidsson & Pettersson, 2012:12; Lai & Li, 2005:377; Liao *et al.*, 2009:313; Tshiwase, 2012:47).

The structured questionnaire (Annexure A) was developed based on similar instruments as cited in the literature (Arvidsson & Pettersson, 2012:12; Lai & Li, 2005:377; Liao *et al.*, 2009:313; Tshiwase, 2012:47). The final version of the questionnaire included 16 items to measure the four constructs of the research model; Perceived Ease of Use (five items), Perceived Usefulness (four items), Attitude towards Using MicroStrategy™ (four items), and Behavioural Intent to Use MicroStrategy™ (three items). All items required five-point Likert-style responses ranging from 1= "Strongly Disagree" to 5= "Strongly Agree".

An approximate study population of 380 users exists within the organisation. These include users currently using the MicroStrategy™ OLAP functionality and users that know about the system but have had limited or no experience using it.

A sample size of 250 users was identified using convenient sampling. Convenient sampling was used due to the availability of respondents, quickness within which data could be gathered and the cost effectiveness of sampling method. Questionnaires were handed out in hard copy to ensure a more successful response rate; the company has a history of low response rate on their electronic survey mechanism (Burger, 2016). A final response rate of 58.4 % was achieved.

In order to test whether the sample would be suitable a Kaiser-Meyer-Olkin (KMO) test was done. The KMO test is a measure of how suitable data is for factor analysis. The test measures are sampling adequacy for each variable in the model and for the complete model (Cerny & Kaiser, 1977:43-47). The Kaiser-Meyer-Olkin (KMO) measure for sampling adequacy was calculated according to Equation 1.1 and the results are displayed in Table 3-1.

$$KMO_j = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} u_{ij}^2} \quad (1.1)$$

Where:

$R = [r_{ij}]$ is the correlation matrix

$U = [u_{ij}]$ is the partial covariance matrix

Table 3-1: Kaiser-Meyer-Olkin measure of sampling adequacy results

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.928
Bartlett's Test of Sphericity	Approx. Chi-Square	2739.487
	df	120
	Sig.	0.000

As seen in Table 3-1, the significant level is less than 0.05 and the Kaiser-Meyer-Olkin measure of sampling adequacy is 0.928. Cenry and Kaiser (1977:43-47) state that the significant (Sig) should be less than 0.05 and a KMO value should be greater than 0.6 in order to define a sample as adequate. A KMO value greater than 0.9 is an excellent result, indicating that the sample data is more than adequate for factor analysis.

3.4 DATA PROCESSING

The frequency analysis, descriptive statistics, reliability and internal consistency of the selected constructs as well as correlations between constructs, and linear regression were tested using IBM SPSS (version 23) software packages by the statistical department of the North-West University.

3.5 CONCLUSION

The South African Pharmaceutical manufacturer participating in this study provides a suitable environment for the research. The organisation has a respectable user base making use of the MicroStrategy™ system with good potential for growth. MicroStrategy™ has proven to be a successful implementation, offering a variety of services to the organisations. On review of the research setting it is clear that a structured questionnaire (Annexure A) would be a satisfactory mechanism to test the theory empirically.

3.6 CHAPTER SUMMARY

This chapter set out to discuss the research methodology followed in order to test whether the Technology Acceptance Model; if applied to a Business Intelligence system, would be able to predict user acceptance through the relationship it proposes, that is, Behavioural intention to use = Perceived Usefulness + Perceived Ease of Use. A structured questionnaire was introduced to a convenient sample of 250 users yielding a response rate of 58.4%. The data was then analysed through various statistics using the IBM SPSS tool. The results of these analyses are discussed in Chapter 4.

CHAPTER 4 RESULTS AND DISCUSSION

4.1 INTRODUCTION

Data was collected using a structured questionnaire, developed as prescribed in Chapter 3. A sample was taken from a South African pharmaceutical organisation using the MicroStrategy™ Business Intelligence system. The data collected was analysed to determine the relationship between variables and different factors.

The theme of this study is the Technology Acceptance Model and its application to Business Intelligence. In particular, its application to the MicroStrategy™ Business Intelligence (BI) system within the South African pharmaceutical environment. In this chapter, the results of data collected and analysed are presented. The focus was to identify if the variables, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) had a positive correlation with Attitude towards Using (ATU) and Intention to Use (ITU). This was done through an analysis of the various correlations, and frequencies. A linear regression was done to test the model on data collected, and emphasis was also added to the demographical variables of: age, gender, division and experience with the Business Intelligence tool.

4.2 DEMOGRAPHICAL PROFILE OF RESPONDENTS

Figure 4-1 to 4-4 displays the demographical profile and representation of the 146 respondents that participated in this study.

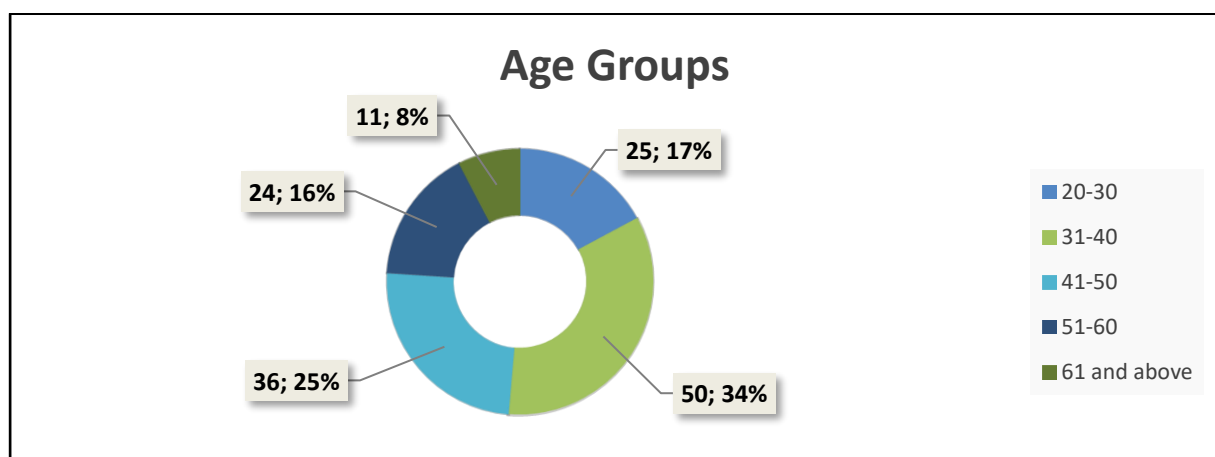


Figure 4-1: Age group representation of respondents

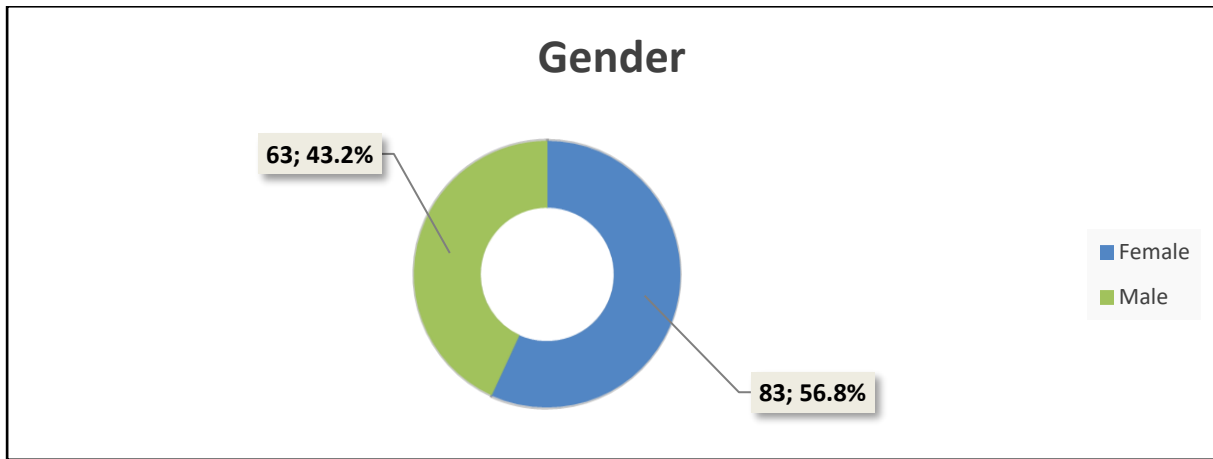


Figure 4-2: Gender representation of respondents

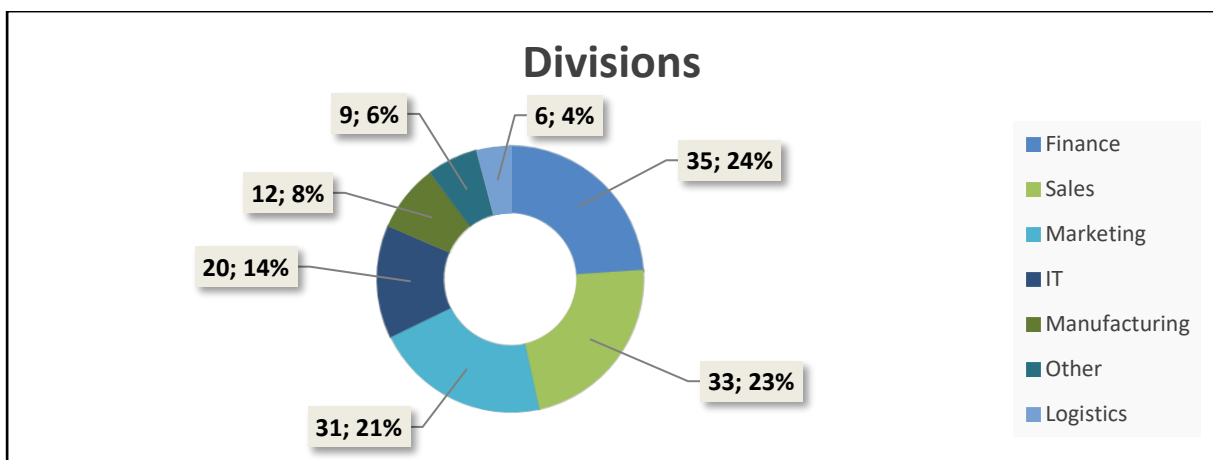


Figure 4-3: Division representation of respondents

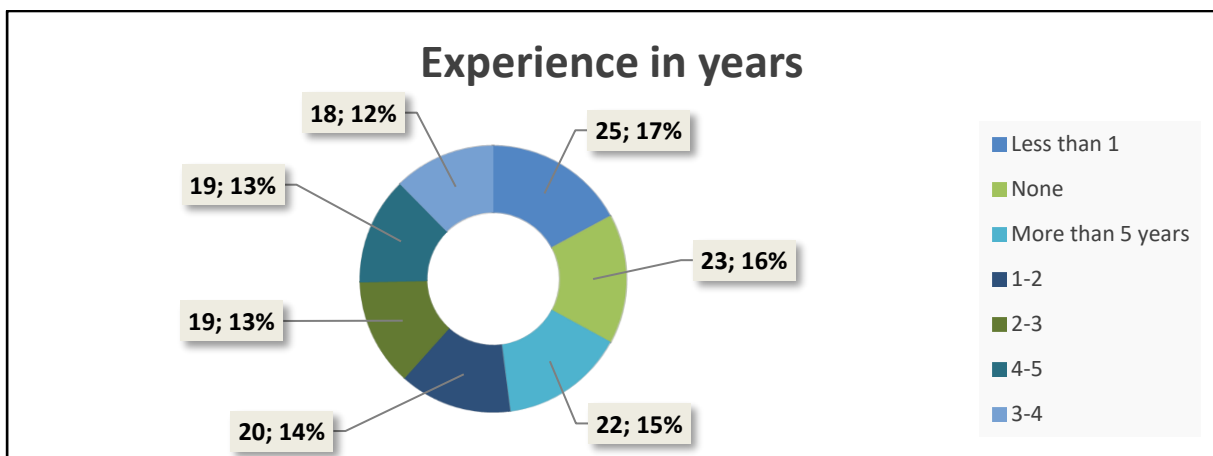


Figure 4-4: Years' experience representation of respondents

As depicted in Figure 4-1, 34% (50) of respondents were between the ages of 31 to 40. 24% and 17% of respondents were between the ages of 41 to 50 and 20 to 30 respectively. Figure 4-2 shows that, of the 146 respondents, 56.8% were female and 43.2% were males. 68% of the users were either in finance (24%), sales (23%) or marketing (21%) as shown in Figure 4-3. This

is an accurate representation of the population as these divisions make up the most of the users, due to their immense requirement of sales data (Reddy, 2016). The respondent's experience with the Business Intelligence tool (Figure 4-4) is distributed virtually evenly, ranging from no online experience but with knowledge of the tool, to more than five years of experience.

4.3 EMPIRICAL STUDY RESULTS

The frequency analysis, descriptive statistics, reliability and internal consistency of the selected constructs as well as correlations between constructs and selected questions were tested using the IBM SPSS software packages and will be discussed in Section 4.3.1 to 4.3.3 below.

4.3.1 Reliability of measuring instruments

In order to determine the reliability and internal consistency of variables measured, a Cronbach alpha coefficient was calculated for each. As a measure of reliability and internal consistency the Cronbach's alpha indicates whether items and subsets of items in the measuring instrument are highly correlated. Cronbach's alpha (α) is, therefore, a coefficient of reliability of items in a survey and represents the quality of the measurement. The value for alpha can vary between zero and one, but a value of 0.7 is the internationally acceptable standard (Welman *et al.*, 2010:147). The Cronbach's alpha for the four constructs all varied between 0.923 & 0.959 as illustrated in Table 4- 1.

Table 4-1: Reliability and internal consistency of constructs

Construct	Cronbach's alpha (α)	Mean	Standard Deviation
Perceived Usefulness (PU)	0.959	4.07	0.748
Perceived Ease of Use (PEOU)	0.923	3.74	0.750
Attitude towards Using (ATU)	0.940	4.09	0.733
Intention to Use (ITU)	0.941	4.18	0.824

All four constructs have high alphas (α) of over 0.900 which is respectable and higher than the international standard. The result is that all four constructs could be used in the study. Perceived Usefulness (PU) has the highest alpha of 0.959.

In an overview of the mean values, it is apparent that Intention to Use (ITU) has the highest value of 4.18. This is a good indication that overall, the sample has a positive intention to use the MicroStrategy™ Business Intelligence tool. Perceived Ease of Use (PEOU) has the lowest mean

of 3.74, which could indicate that the system is not easy to use or user-friendly. Overall, the reaction to all constructs is positive considering the five-point Likert-scale.

The average standard deviation across all constructs was 0.764, fluctuating between 0.733 and 0.824. The highest standard deviation was Intention to Use (0.824).

4.3.2 Analysis of constructs

Within this section, the relevance of the questions and the results obtained for each construct will be analysed and discussed. This will be done for each of the four constructs, that is, Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude towards Using (ATU), and Intention to Use (ITU). Each construct and their questions were measured on a five-point Likert scale (as seen in Table 4-2).

Table 4-2: Five-point Likert scale

1	2	3	4	5
Strongly Disagree	Disagree	Neither Disagree not Agree	Agree	Strongly Agree

4.3.2.1 Analysis of Perceived Usefulness (PU)

As illustrated in Table 4-3, all participants (146) completed each of the five Perceived Usefulness questions in this section. With a construct mean of 4.07, participants responded positively towards Perceived Usefulness (PU). Thus the respondents had an overall perception that using the Business Intelligence tool would produce a better outcome regarding: performance, productivity, effectiveness and making better decisions. The lowest mean for this construct was question 2 (PU2) of 3.99. The question: “Using the MicroStrategy Business Intelligence tool improves my productivity”. This could be attributed to a more negative response on Perceived Ease of Use (PEOU). The highest mean value (4.21) was question 4 (PU4), “I find the MicroStrategy Business Intelligence tool to be useful”. This is ultimately a summary of the construct and corresponds to the literature, in that a system should be useful to the user (Arvidsson & Pettersson, 2012:8). It is also important to note that question 5 (PU5) also concurs with literature, “Using MicroStrategy Business Intelligence tool enables me to make better decisions”. According to Sparks and McCann (2015:31-32) a core function of a Business Intelligence system should be to increase decision-making capability.

Table 4-3: Perceived Usefulness (PU) frequency

Question	Respondents	Mean	Std. Deviation
PU1	146	4.03	0.783
PU2	146	3.99	0.843
PU3	146	4.03	0.817
PU4	146	4.21	0.772
PU5	146	4.10	0.816
Total	146	4.07	0.748

4.3.2.2 Analysis of Perceived Ease of Use (PEOU)

Table 4-4 shows that all participants (146) completed each of the four questions in this section. With a construct mean of 3.74 and standard deviation of 0.75, Perceived Ease of Use (PEOU) had a less positive response than PU, which could indicate that the respondents do not find the system very user-friendly or difficult to master. The respondents are thus between, neither disagree nor agree and agree regarding whether the MicroStrategy Business Intelligence tool is easy to use and free of effort. The question with the least positive response, which is also the question summarising the construct, was question 1 (PEOU1): “Learning to use the MicroStrategy Business Intelligence tool is easy and free of effort for me”. This question had a mean value of only 3.68.

The result from PU and PEOU correlates to a study done by Arvidsson and Pettersson (2012:15), where similar results were obtained for a Business Intelligence tool (Qlickview). In the study, PU has a higher mean value than PEOU but both are still positive.

Table 4-4: Perceived Ease of Use (PEOU) frequency

Question	Respondents	Mean	Std. Deviation
PEOU1	146	3.68	0.837
PEOU2	146	3.73	0.841
PEOU3	146	3.77	0.803
PEOU4	146	3.77	0.847
Total	146	3.74	0.750

4.3.2.3 Analysis of Attitude towards Using (ATU)

Overall respondents had a positive Attitude towards Using (ATU) the MicroStrategy Business Intelligence tool (Table 4-5), with a construct mean of 4.09 and standard deviation of 0.733. The lowest mean was calculated on question 3 (ATU3): “Using the MicroStrategy Business Intelligence tool would be a pleasant experience”. Even though the question was still answered

positively, the lower mean could be ascribed to the correspondingly low PEOU. Table 4-6 illustrates the correlation between Question 3 (ATU3) and the two constructs (PU & PEOU). Question 3 has a statistical significant correlation of 0.593 with the construct Perceived Ease of Use (PEOU).

Table 4-5: Attitude towards Using (ATU) frequency

Question	Respondents	Mean	Std. Deviation
ATU1	146	4.18	0.733
ATU2	146	4.18	0.811
ATU3	146	3.93	0.868
ATU4	146	4.08	0.766
Total	146	4.09	0.733

Table 4-6: PU and PEOU correlation with ATU3

			ATU3
Spearman's rho	PU	Correlation Coefficient	.558**
		Sig. (2-tailed)	.000
		N	146
	PEOU	Correlation Coefficient	.593**
		Sig. (2-tailed)	.000
		N	146

**. Correlation is significant at the 0.01 level (2-tailed).

4.3.2.4 Analysis of Intention to Use (ITU)

The respondents have a positive Intention to Use (ITU) the MicroStrategy™ Business Intelligence tool. As illustrated in Table 4-7 the construct mean of 4.18 and standard deviation of 0.824. This is the highest mean recorder between the four constructs. The positive Intention to Use (ITU) is valuable result as a person's behavioural intention is strongly related to the person's actual behaviour; in other words, if a person intends to behave in a particular manner, it is likely that they will end up acting in this manner (Farahat, 2012:97).

Table 4-7: Intention to Use (ITU) frequency

Question	Respondents	Mean	Std. Deviation
ITU1	146	4.19	0.873
ITU2	146	4.16	0.910
ITU3	146	4.18	0.828
Total	146	4.18	0.824

4.3.3 Correlation of constructs

Spearman's rho (ρ) correlation, is a nonparametric equivalent of the Pearson correlation and a technique that measures the linear correlation between two variables. A positive correlation between two constructs implies that, if one construct increases, the other one increases as well (Welman *et al.*, 2010:234).

Table 4-8: Spearman's rho's and p-values for constructs

			PU	PEOU	ATU	ITU
Spearman's rho	PU	Correlation Coefficient	1.000	.509**	.643**	.600**
		Sig. (2-tailed)		.000	.000	.000
	PEOU	Correlation Coefficient	.509**	1.000	.624**	.501**
		Sig. (2-tailed)	.000		.000	.000
	ATU	Correlation Coefficient	.643**	.624**	1.000	.809**
		Sig. (2-tailed)	.000	.000		.000
	ITU	Correlation Coefficient	.600**	.501**	.809**	1.000
		Sig. (2-tailed)	.000	.000	.000	

** . Correlation is significant at the 0.01 level (2-tailed).

Table 4-8 shows that all constructs have a positive and statistically significant correlation with one another. The most noteworthy correlation exists between Attitude towards Using (ATU) and Intention to Use (ITU) with a correlation coefficient of 0.809. Consistent with prior research on the Technology Acceptance Model, a statistically significant correlation exists between Perceived Usefulness (PU), Perceived Ease of Use (PEOU) and Intention to Use (ITU). This supports literature findings that the Technology Acceptance Model is a good model for evaluating Behavioural intention to use (Lai & Li, 2005:383).

An effect sizes analysis was done to investigate any statistically significant differences in results when comparing demographical groups. The only significant results were on PEOU and is illustrated in Table 4-9 and Table 4-10.

Table 4-9: Effect size analysis on PEOU and department

		N	Mean	Std. Deviation	Effect sizes			
					Finance	Marketing	Sales	IT
PEOU	Finance	35	3.6714	.91509				
	Marketing	31	3.6694	.64996	0.00			
	Sales	33	3.7424	.55370	0.08	0.11		
	IT	20	4.0000	.76520	0.36	0.43	0.34	
	All Other	27	3.7130	.82539	0.05	0.05	0.04	0.35
	Total	146	3.7397	.74964				

Table 4-9 shows a significant difference in the respondent's answers to PEOU when comparing IT to other departments. IT has a higher mean than other divisions indicating that these respondents overall perceive the systems to be easy to use. This could be due to the fact the IT employees are more computer literate or have come across a larger variety of systems, making them more confident that they will find the system easy to use.

Table 4-10: Effect size analysis on PEOU and age

		N	Mean	Std. Deviation	Effect sizes		
					20 - 30	31 - 40	41 - 50
PEOU	20 - 30	25	3.9700	.74414			
	31 - 40	50	3.8500	.71250	0.16		
	41 - 50	36	3.5625	.68498	0.55	0.40	
	51 and above	35	3.6000	.82516	0.45	0.30	0.05
	Total	146	3.7397	.74964			

Table 4-10 indicates a significant difference in respondents' PEOU subject to their age. The results revealed that younger respondents perceive the system easier to use than older respondents. This could be ascribed to the younger generation growing up with technology, their quick adoption rate of new technology, a more flexible approach to changes in technology and systems.

In addition to Spearman's rho (correlation coefficient) and effect sizes, linear regressions were done to test the model and conclude whether, as correlations indicated, Perceived Usefulness (PU) + Perceived Ease of Use (PEOU) = Attitude towards Using (ATU) and Intention to Use (ITU). Levine *et al.*, (2011:556) explain that a multiple regression analysis is used to measure the effect that two or more independent variables have on a dependent variable.

Table 4-11: Linear regression for dependent variable: Attitude towards Using

Model	Unstandardized Coefficients		Standardized Coefficients	t - value	p- Value.
	B	Std. Error	Beta		
1 (Constant)	.702	.227		3.092	.002
PU	.497	.062	.507	7.989	.000
PEOU	.366	.062	.374	5.896	.000

- a. Dependent Variable: ATU
b. $R^2 = 0.616$

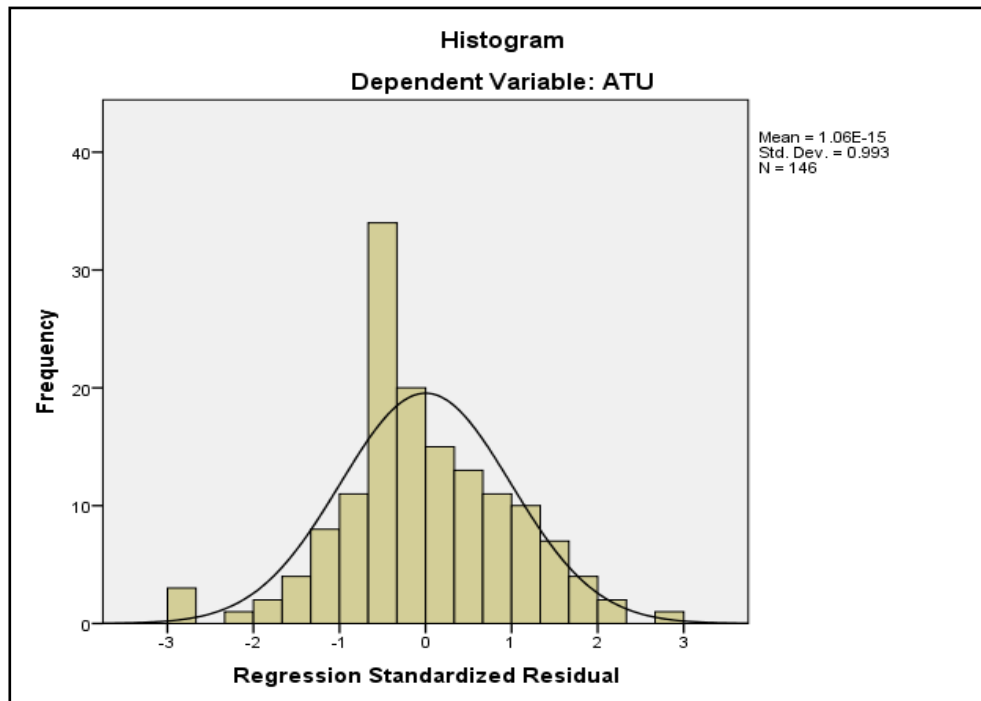
**Figure 4-5: Linear regression histogram (dependant variable Attitude towards Using)**

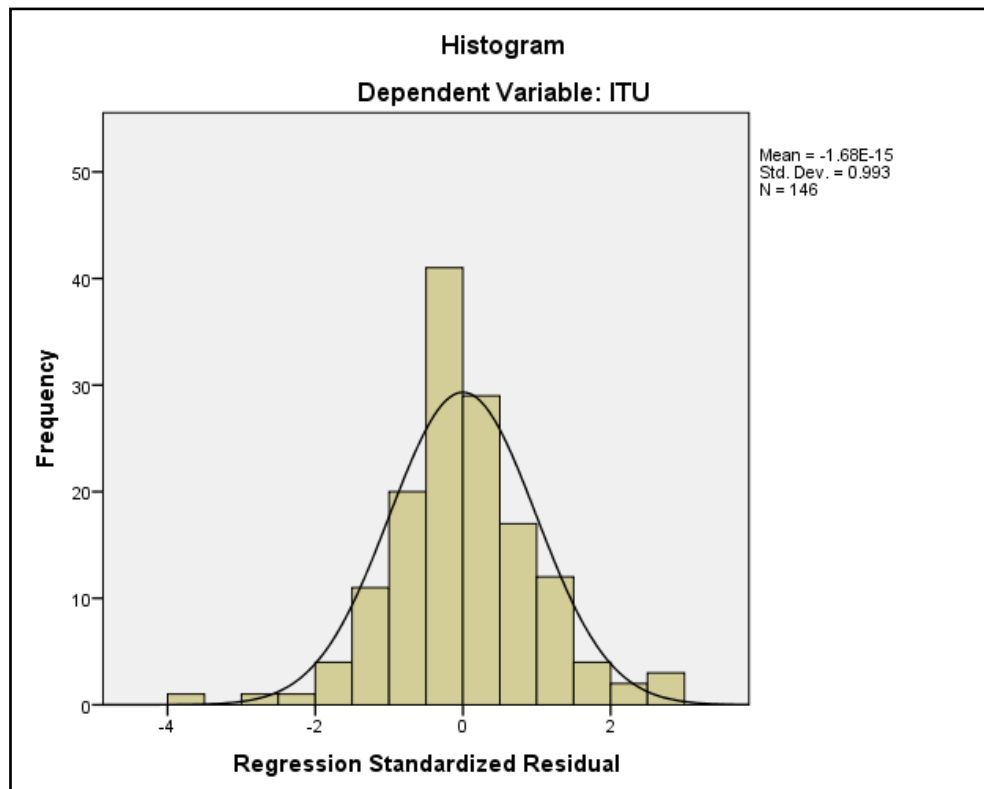
Table 4-11 and Figure 4-5 show the results of linear regression done on independent variables, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) and the dependant variable Attitude towards Using (ATU). This was done to determine whether the variation in ATU could be explained by PU and PEOU. The regression yielded a normal distribution with an R^2 of 0.616 indicating that 61.6% of the variation in ATU can be explained by the variables PU and PEOU. Both these variables are statistically significant in predicting ATU (p- values less than 0.05), with PU being able to explain more of the variance with a Beta of 0.507 compared to PEOU (Beta = 0.374).

Table 4-12 and Figure 4-6 show the results of the linear regression done on independent variables, Perceive Usefulness (PU) and Perceived Ease of Use (PEOU) and the dependent variable Intention to Use (ITU). The reason for this linear regression test is to determine whether the variation in ITU could be explained by PU and PEOU.

Table 4-12: Linear regression for dependent variable: Intention to Use

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	.783	.291		2.688	.008
PU	.627	.080	.569	7.853	.000
PEOU	.225	.080	.205	2.825	.005

- a. Dependent Variable: ITU
b. $R^2 = 0.500$

**Figure 4-6: Linear regression histogram (dependant variable Intention to Use)**

The regression model also yielded a normal distribution with an R^2 of 0.500 indicating that 50.0% of the variation in ITU can be explained by the variables PU and PEOU. In this model the variables explain less of the variation in ITU compared to ATU but both PU and PEOU are still statistically significant (p- values less than 0.05), with PU being able to explain more of the variance with a Beta of 0.569 compared to PEOU (Beta = 0.205). In a study done by King and He (2006:746) a meta-analysis was done on the Technology Acceptance Model. They found that after comparing 67 research papers, most yielded the same result as above, where the PEOU explained less of the result than PU. King and He (2006:746) goes on to state that of the 67 research papers, only 30 had a result where PEOU was statistically significant. Even though both linear regressions yielded a normal distribution, ATU had a wider spread than ITU indicating a larger standard deviation.

The results of both these regressions correspond to the literature finding in that the Technology Acceptance Model defines the relationship between the two main constructs, Perceived usefulness (PU) and Perceived Ease of Use (PEOU) as positive and theorised that they are determinants of user acceptance (Farahat, 2012:97).

4.4 CONCLUSION

In this chapter the results of the empirical research study were analysed and presented. The explanation of the results started with an analysis of a demographic profiling of the respondents. These findings indicated that 34% of respondents were between the ages of 31 to 40. There was a fairly even split between male and female as well as an even spread across all buckets of “experience with the Business Intelligence tool”. An interesting finding was that 68% of the users were either in finance (24%), sales (23%) or marketing (21%). Secondly, the data gathered was tested for reliability. All constructs yielded a Cronbach’s alpha between 0.923 & 0.959, which is well above the internationally accepted standard of 0.7.

Thirdly, each construct and its underlying questions were examined individually to establish which questions stood out and what the overall perception was of each construct. The results indicated that respondents “Agreed” to “Strongly Agreed” that they had a positive perception that the MicroStrategy™ Business Intelligence Tool was useful. A lower response was received when testing whether or not the respondents perceived the Business Intelligence Tool to be easy to use. Overall respondents had a positive attitude towards using the system and an even higher response to intention to use.

Fourthly correlations were done between constructs to see how much of the variation could be explained. The findings matched the literature in that an exceptionally strong correlation exists between Attitude towards Using and Intention to Use. 81% of this variation could be explained. Statistically significant correlations existed between Perceived Usefulness and Attitude towards Using and Intention to Use, both greater than 60%. Perceived Ease of Use also yielded statistically significant correlations with Attitude towards Using and Intention to Use but lower than that of Perceived Usefulness.

Lastly, a linear regression model was created to test the Technology Acceptance Model as a whole that is, Behavioural intention to use = Perceived Usefulness + Perceived Ease of Use. This was found to be true and statistically significant with the model resulting in an R^2 of 0.500. Perceived Usefulness was the biggest contributor to explaining variances within the model.

4.5 CHAPTER SUMMARY

The aim of Chapter 4 was to analyse the data received from respondents and to determine whether the Technology Acceptance Model could explain user acceptance in Business Intelligence. In order to do this, the chapter focused on the empirical research findings of the study. A frequency analysis, descriptive statistics, reliability and the internal consistency as well as correlations between constructs and questions were tested using the SPSS software packages. The results were discussed and compared to previous literature and research results.

The Technology Acceptance Model was validated using a linear regression model applied to the respondent feedback. The results of the analysis were positive, with the model being able to explain more than 50% of the variance in Intention to Use through the two constructs that is, Perceived Usefulness and Perceived Ease of Use.

CHAPTER 5 CONCLUSION AND RECOMMENDATIONS

5.1 INTRODUCTION

The primary objective of this study was to validate the Technology Acceptance Model in its ability to determine user acceptance with in a Business Intelligence setting. Secondary to this objective was to investigate this within the South African pharmaceutical environment. Lastly was to examine the relationship between the two constructs driving the model that is, Perceived Usefulness and Perceived Ease of Use.

The literature review in Chapter 2 set out to define user acceptance and the need for it to be tested. It highlighted the Technology Acceptance Model as an acknowledged and validated model, not yet tested on Business Intelligence (BI). The chapter also motivated why it the Technology Acceptance Model should be the starting point for new user acceptance research. The Technology Acceptance Model and its constructs were discussed in detail as well as the role played by user satisfaction. Information systems, Business Intelligence and the architecture behind Business Intelligence were defined and discussed. Lastly, a timeline was depicted of how Business Intelligence evolved from a once IT driven function, to the need for “Business Intelligence for the Masses”.

Chapter 3 developed a research methodology to test whether the Technology Acceptance Model would be a valid measure of user acceptance when applied to Business Intelligence. This methodology was the analysed and the results deliberated in Chapter 4.

Chapter 5 would be devoted to drawing conclusions from the literature review as discussed in Chapter 2 and the empirical study as reported on in Chapter 3 - 4. Subsequent recommendations for future reassurance and studies will also be presented.

5.2 CONCLUSION TO A VALIDATION OF THE TECHNOLOGY ACCEPTANCE MODEL ON BUSINESS INTELLIGENCE SYSTEMS IN A SOUTH AFRICAN PHARMACEUTICAL ORGANISATION

The general objective of this research as stated in Section 1.6.1, was to validate the Technology Acceptance Model (TAM) and to determine whether the comprehensive research model can be instrumental in predicting the level of commitment of Business Intelligence end users in accepting,

using and exploiting the MicroStrategy™ system. This objective was realised through both the literature review and the empirical research. The literature revealed that the Technology Acceptance Model is one of the most important, used and tested theories studying user acceptance of information systems. The model, with its simple and avid nature, provides the optimal starting point for user acceptance research. The empirical research tested the model through both standalone correlations of each construct as well as a linear regression of the model, first testing the impact of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) on Attitude towards Using (ATU). Secondly testing Perceived Usefulness and Perceived Ease of Use on Behavioural Intention to Use.

The first regression yielded an R^2 of 0.616 indicating that 61.6% of the variation in Attitude towards Using (ATU) could be explained by the variables PU and PEOU. Both these variables were statistically significant, with PU being able to explain more of the variance with a Beta of 0.507 compared to PEOU with a Beta = 0.374. The second regression model yielded an R^2 of 0.500 indicating that 50.0% of the variation in Intention to Use (ITU) could be explained by the variables PU and PEOU. Although this result of ITU was lower than that of ATU the results were still statistically significant and far higher than most studies applying the model to other Information Technologies. Through the model, PU was able to explain more of the variance with a Beta of 0.569 compared to PEOU with a Beta of 0.205.

The results of these regression models provide sound evidence that the Technology Acceptance Model can predict the level of commitment towards a Business Intelligence system in users accepting and using the system. The model can thus be used industrialised to test other organisations and Business Intelligence systems as well as retest the study organisation to determine changes in user acceptance levels.

Secondary objectives were set in Section 1.6.2 of:

- Validate the Technology Acceptance Model within the South African Pharmaceutical Business Intelligence user environment.
- Study the relationship between the Perceived Usefulness and Perceived Ease of Use, as well as their contribution towards attitude towards using and intention to usage.

Both these objectives were realised. Firstly, the Technology Acceptance Model was validated within the South African Pharmaceutical Business Intelligence user environment. The South African pharmaceutical organisation and Business Intelligence tool (MicroStrategy™) proved to be perfect candidates; yielding not only statistically significant correlation between all constructs about the Technology Acceptance Model but also explaining the majority of the variations on both ATU and ITU.

Secondly, the relationship between the Perceived Usefulness and Perceived Ease of Use, as well as their contribution towards attitude towards using and intention to usage was tested. The results showed that all four constructs have a positive and statistically significant relationship with the most noteworthy correlation existing between ATU and ITU which produced a correlation coefficient of 0.809. Consistent with prior research on the Technology Acceptance Model, a statistically significant positive correlation existed between PU and PEOU. From the literature, as well as the research results it is evident that PEOU does not always have a high correlation with other constructs. This is because users will be willing to use a system even if it is not easy to use as long as they find it useful.

The study also revealed interesting findings that were not part of the initial objectives, such as:

- From the literature, it is apparent that Business Intelligence and Business Intelligence tools, in general, are moving towards a wider spread and more user orientated environment.
- The literature also revealed that social media, smartphones, RFID and disruptive technologies are creating masses of data and to a large extent unstructured data, pushing IT towards Big Data at a rapid pace.
- Empirical results highlighted that within pharmaceutical organisations, sales and market data is predominantly utilising the Business Intelligence setting.
- From both the literature and empirical results, it is evident that the Technology Acceptance Model has stood the test of time. Enabling not only user acceptance testing but also providing a platform to enrich and elaborate on user acceptance research.

5.3 LIMITATIONS AND RECOMMENDATIONS FOR FUTURE STUDIES

This mini-dissertation is concluded by highlighting the limitation of the study and proposing recommendations for future studies and research.

Throughout the literature, it is evident that limited research has been done on user acceptance of Business Intelligence. This study only focussed on one particular OLAP Business Intelligence tool (MicroStrategy™) within a pharmaceutical organisation. Future research could include other tools or organisation in different industries and compare results.

Due to the avid and simple nature of the Technology Acceptance Model, it easily lends itself to adaptations. This study tested the original model, to validate it. Future research could add

additional constructs or variables to the model to test other aspects impacting Business Intelligence. Variables picked up in the study included training, user satisfaction, change management and various subject norms. One aspect of this study which did not yield statistical significant results, was the construct of experience. However throughout the literature training and experience proved to have significant impact. Thus the construct of experience with the Business Intelligence tool as well as training would serve as valuable further research.

The study also allows itself to be replicated using the same research setting after a management intervention of change management or training to increase Perceived Usefulness (PU) and Perceived Ease of Use (PEOU).

The study, although successful in validating the model and providing insights on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) to the organisation in question, could be applied to other organisation in the pharmaceutical industry to establish a better interpretation of the industry as a whole.

5.4 CONCLUSION

The aim of this study was to validate the Technology Acceptance Model in its ability to determine user acceptance within a Business Intelligence. This objective was realised through firstly, a literature review, and secondly, through empirical research results. The results provided clear indication that the majority of variance could be explained through the model's constructs. The secondary objectives were also achieved, in that the pharmaceutical environment proved to be a good candidate for Business Intelligence user acceptance testing and respectable correlations were generated amounts all constructs about the Technology Acceptance Model.

This study validated the model in its original form. The model does lend itself to further research by either expanding on the model or expanding on the research setting. The conclusion of this study has a managerial impact in the sense that the results can be used by the organisation to better manage their user acceptance. It also allows the organisation to retest and compare results after interventions have been taken

5.5 CHAPTER SUMMARY

In this chapter, the findings of the literature review as well as the survey used in the empirical research, were summarised and related to the objectives of the study. The objectives and their results were discussed. Noteworthy findings were also mentioned to further research on Business Intelligence user acceptance.

Recommendations for future research as well as the limitations relating to this study were addressed. This will hopefully encourage and advance the research of Business Intelligence user acceptance by both academia and corporate managers.

BIBLIOGRAPHY

- Abbasi, A., Sarker, S. & Chiang, R.H.L. 2016. Big data research in information systems: toward an inclusive research agenda. *Journal of the association for information systems*, 17:1-33.
- Agarwal, R. 2000. Individual acceptance of information technologies. (In Zmud, R.W. ed. Framing the domains of IT management: projecting the future through the past, Cincinnati: OH: Pinnaflex educational resources. p. 85-104.
- Alpar, P. & Schulz, M. 2016. Self-service business intelligence. *Business and information system engineering*. 58:151-155.
- Amadi-Echendu, J.E. & De Wit, F.C.P. 2015. Technology adoption: a study on post-implementation perceptions and acceptance of computerised maintenance management systems. *Technology in society*. 43: 209-218.
- Arvidsson, P. & Pettersson, D. 2012. Usage of business intelligence: testing the technology acceptance model on a BI system. Uppsala: Uppsala University. (Thesis - Masters).
- Baiju, N.T. 2014. Top business intelligence (BI) tools in the market. <http://bigdata-madesimple.com/top-business-intelligence-bi-tools-in-the-market/> Date of access: 25 Oct. 2016.
- Baltzan, P. 2015. Business driven technology. 6th ed. Denver, CO: McGraw Hill.
- Bliscorecard. 2014. BI Scorecard: strategic and product summary. https://www.microstrategy.com/Strategy/media/downloads/about-us/BI-scorecard-summary_Q4-2014.pdf Date of access: 30 Oct. 2016.
- Böhringer, M., Gluchowski, P., Kurze, C. & Schieder, C. 2010. A business intelligence perspective on the future internet. (In 16th Americas conference on information systems. Peru: Association for information systems. p. 267-277).
- Botha, E. 2012. Information technology governance frameworks in higher education in South Africa: a paradigm shift. Potchefstroom: North-West University. (Thesis - MBA).
- Burger, J. 2016. Technical administrator [personal interview]. 31 Oct. South Africa.

- Capece, G. & Campisi, D. 2013. User satisfaction affecting the acceptance of an e-learning platform as a mean of the development of the human capital. *Behavioural and information technology*, 32: 335-343.
- Cerny, C.A. & Kaiser, H.F. 1977. A study of a measure of sampling adequacy for factor-analytic correlation matrices. *Multivariate behavioral research*, 12:43-47.
- Chuttur, M.Y. 2009. Overview of the technology acceptance model: origins, developments and future directions. *Working papers on information systems*, 9:9-37.
- Davis, F.D. 1986. *A technology acceptance model for empirically testing new end-user information systems: theory and results*. Wayne State University: Massachusetts institute of technology. (Thesis - PhD).
- Du Plessis, D.P. 2012. Implementing business intelligence processes in a telecommunications company in South Africa. Vanderbijlpark: North-West University. (Thesis - PhD).
- Erasmus, E. 2014. Technology acceptance, psychological attachment and technostress. Vanderbijlpark: North-West University. (Thesis - PhD).
- Falaleeva, N.G. & Johnson, R.D. 2002. Influence of individual psychological traits on attribution towards computing technology. (*In* Proceeding of the 8th Americas conference on information systems. Dallas. p. 1028-1033).
- Farahat, T. 2012. Applying the technology acceptance model to online learning in the Egyptian universities. *Procedia social and behavioral sciences*, 64:95-104.
- Gartner. 2016. Critical capabilities for business intelligence and analytical platforms. <https://www.gartner.com/doc/reprints?id=1-327QBQX&ct=160330&st=sb> Date of access: 30 Oct. 2016.
- Hashem, I.A.T., Yaqoob, I., Anuar, N.B., Mokhtar, S., Gani, A. & Khan, S.U. 2015. The rise of "big data" on cloud computing: review and open research issue. *Information systems*, 47:98-115.
- Hou, C. 2014. User acceptance of business intelligence systems in Taiwan's electronics industry. *Social behavior and personality*, 4:583-596.

- Johansson, B., Alkan, D. & Carlsson, R. 2015. Self-service BI does it change the rule of the game for BI systems designers. (*In 8th workshop on information logistics and knowledge supply* vol 1420. p. 48-61).
- Kim, Y.J., Chun, J.U. & Song, J. 2009. Investigating the role of attitude in technology acceptance from an attitude strength perspective. *International journal of information management*, 29:67-77.
- King, W.R. & He, J. 2006. A meta analysis of the technology acceptance model. *Information & management*, 43:740-755.
- Kisielnicki, J. & Misiak, A.M. 2016. Effectiveness of agile implementation methods in business intelligence. *The international journal of an emerging transdiscipline projects from an end-user perspective*, 19:161-172.
- Lai, V.S. & Li, H. 2005. Technology acceptance model for internet banking: an invariance analysis. *Information & management*, 42:373-386.
- Larson, D. & Chang, V. 2016. A review and future direction of agile, business intelligence, analytics and data science. *International journal of information management*, 36:700-710.
- Lee, M.K.O., Cheung, C.M.K. & Chen, Z. 2005. Acceptance of Internet-based learning medium: the role of extrinsic and intrinsic motivation. *Information & management*, 42:1095-1104.
- Lee, Y., Kozar, K.A. & Larsen, K.R.T. 2003. The technology acceptance model: past, present and future. *Communications of the association for information systems*, 12:752-780.
- Legris, P., Ingham, J. & Colletette, P. 2003. Why do people use information technology? a critical review of the technology acceptance model. *Information & management*, 40:191-204.
- Levine, D.M., Stephan, D.F., Krehbiel, T.C. & Berenson, M.L. 2011. Statistics for managers using Microsoft Excel. 6th ed. Upper Saddle River, NJ: Pearson Education.
- Liao, C., Palvia, P. & Chen, J. 2009. Information technology adoption behavior life cycle: toward a technology continuance theory (TCT). *International journal of information management*, 29:309-320.
- Liu, S.H., Liao, H.L. & Pratt, J.A. 2009. Impact of media richness and flow on e-learning technology acceptance. *Computers & education*, 52:599-607.

Lloyd, J. 2011. Identifying key components of business intelligence systems and their role in managerial decision making. Eugene, OR: University of Oregon. (Thesis - M.Sc).

Marjanovic, O. 2007. The next stage of operational business intelligence: creating new challenges for business process management. (In 40th annual hawaii international conference on system sciences. *IEEE The computer society*. p. 215C).

Masrom, M. 2007. Technology acceptance model and e-learning. (In 12th international conference on education. Darussalam: University Brunei Darussalam. p. 1-10).

MicroStrategy™ Incorporated. 2016a. *MicroStrategy™*.

<https://www.microstrategy.com/us/company/overview> Date of access: 30 Oct. 2016.

MicroStrategy™ Incorporated. 2016b. *Microstrategy™*.

<http://www2.microstrategy.com/producthelp/10.5/manuals/en/DashboardsAndWidgets.pdf> Date of access: 6 Nov. 2016.

Mikroyannidis, A. & Theodoulidis, B. 2010. Ontology management and evolution for business intelligence. *International journal of information management*, 30:559-566.

Miller, S., McRobbie, G. & Begg, C. 2016. Business intelligence tools: should they be "gamified"? (In SAI computing conference 2016. London. p. 758-763).

Olszak, C.M. & Ziemba, E. 2012. Critical success factors for implementing business intelligence systems in small and medium enterprises on the example of Upper Silesia, Poland. *Interdisciplinary journal of information, knowledge, and management*, 7:129-150.

Park, S.Y. 2009. An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. *Journal of educational technology & society*, 12:150-162.

Petter, S., Delone, W. & McLean, E.R. 2014. Information systems success: the quest for the independent variables. *Journal of management information systems*, 29:7-62.

Reddy, N.J. 2016. MicroStrategy administrator [personal interview]. 31 Oct. South Africa.

Schlegel, K. 2015. Hype cycle for business intelligence and analytics. <https://www.gartner.com/doc/3106118/hype-cycle-business-intelligence-analytics>. Date of access: 01 Aug. 2016.

- Sparks, B.H. & McCann, J.T. 2015. Factors influencing business intelligence system use in decision making and organisational performance. *International journal of Sustainable strategic management*, 5:31-55.
- Straub, D., Limayem, M. & Karahanna, E. 1995. Measuring system usage: implications for IS theory testing. *Management science*, 8:1328-1342.
- Tshiwase, M.V. 2012. Acceptance model and use of technology in the technology and science domain. Vereeniging: North-West University. (Thesis - MBA).
- Van Der Heijden, H. 2004. User acceptance of hedonic information systems. *Management of information systems quarterly*, 28:695-704.
- Venkatesh, V. & Davis, F.D. 2000. A theoretical extension of the technology acceptance model: four longitudinal field studies. *Management science*, 42:186-204.
- Viswanath, V. & Davis, F.D. 1996. A model of the antecedents of perceived ease of use: development and test. *Decision sciences*, 27:451-481.
- Watson, H.J. & Wixom, B.H. 2007. The current stare of business intelligence. *IT system perspectives*, 40:96-99.
- Welman, C., Kruger, F. & Mitchell, B. 2010. *Research methodology*. 3rd ed. Cape Town: Oxford Southern Africa.
- Wixom, B.H. & Todd, P.A. 2005. A theoretical integration of user satisfaction and technology acceptance. *Information system research*, 16: 85-102.
- Wu, L., Barash, G. & Bartolini, C. 2007. A service-oriented architecture for business intelligence. (In International conference on service-oriented computing and applications. IEEE. p. 279-285).
- Yeoh, W. & Koronios, A. 2010. Critical success factors for business intelligence systems. *Journal of computer information systems*, 50:23-32.
- Young Lee, D. & Lehto, M.R. 2013. User acceptance of YouTube for procedural learning: an extension of the technology acceptance model. *Computers & education*, 61:193-208.
- Yousafzai, S.Y., Foxall, G.R. & Pallister, J.G. 2007. Technology acceptance: a meta-analysis of the TAM: part 1. *Journal of modelling in management*, 2:251-290.

Zhang, J. & Mao, E. 2008. Understanding the acceptance of mobile SMS advertising among young Chinese consumers. *Psychology & marketing*, 25:787-805.

ANNEXURE A

Dear Respondent

The purpose of this study is to determine whether the Technology Acceptance Model can be used to determine user acceptance of a Business Intelligence tools. This will be achieved through a survey, requiring participants to answer questions (on a scale of 1 to 5) regarding the MicroStrategy BI tool and their experience with it. MicroStrategy™ is the online analytical platform and reporting tool used in the organisation.

The survey should not take more than 5 minutes to complete. The results of the study will be published in an MBA dissertation through the North-West University, which could be made available to participants after publication.

Biographical information: Please indicate your answer by making a cross in the relevant block.

1	Age (in years):	20-30	31-40	41-50	51-60	61 and above		
2	Gender:	Male	Female					
4	Division:	Finance	Marketing	Sales	IT	Logistics	Manufacturing	Other:
5	Experience with MicroStrategy™ (in years)	None	less than 1	1-2	2-3	3-4	4-5	More than 5

Please answer the following question on a scale of 1 - 5 (1 = Strongly Disagree; 5 = Strongly Agree)

Perceived Usefulness (PU)

Perceived Usefulness refers to the extent to which you trusts that using MicroStrategy™ will produce a better outcomes

- PU1 Using the MicroStrategy™ BI Tool improves my performance
- PU2 Using the MicroStrategy™ BI Tool improves my productivity
- PU3 Using the MicroStrategy™ BI Tool enhances my effectiveness
- PU4 I find the MicroStrategy™ BI Tool to be useful
- PU5 Using the MicroStrategy™ BI Tool enables me to make better decisions

Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly Agree
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5

Perceived Ease of Use (PEOU)

Perceived Ease of Use refers to your perception that using MicroStrategy™ would be easy and free of effort

- PEOU1 Learning to use the MicroStrategy™ BI Tool is easy and free of effort for me
- PEOU2 It is easy to use the MicroStrategy™ BI Tool to accomplish my tasks
- PEOU3 I would find it easy to become skilful in using the MicroStrategy™ BI Tool
- PEOU4 Overall, I believe the MicroStrategy™ BI Tool is easy to use

Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly Agree
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5

Attitude towards using (ATU)

Attitude towards using refers to your point of view towards using MicroStrategy™

- ATU1 Using the MicroStrategy™ BI Tool in my job would be a good idea
- ATU2 I like the idea of using the MicroStrategy™ BI Tool in my job
- ATU3 Using the MicroStrategy™ BI Tool would be a pleasant experience
- ATU4 Overall, my attitude towards the MicroStrategy™ BI Tool is favourable

Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly Agree
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5

Intention to use (ITU)

Intention to use refers to your intention to use MicroStrategy™

ITU1 I would like to use the MicroStrategy™ BI Tool on a regular basis
 ITU2 I would like to use the MicroStrategy™ BI Tool in the future
 ITU3 I will strongly recommend others to use the MicroStrategy™ BI Tool

Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly Agree
1	2	3	4	5
1	2	3	4	5
1	2	3	4	5

ANNEXURE B



Dynamic Language &
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Tuesday, 22 November 2016

To whom it may concern,

Re: Letter of confirmation of language editing

The dissertation: **A validation of the technology acceptance model on BI systems in a South African pharmaceutical organisation** by JJ de Villiers (20742355) was language, technically and typographically edited. The citations, sources and referencing technique applied was also checked to comply with North-West University's guidelines. Final corrections as suggested remain the responsibility of the student.

Yours sincerely,

Antoinette Bisschoff

Officially approved language editor of the NWU since 1998
Member of SA Translators Institute (no. 100181)

Precision ... to the last letter