THE USE AND IMPACT OF BUSINESS INTELLIGENCE (BI) SYSTEMS IN MANAGEMENT ACCOUNTING: AN EMPIRICAL STUDY IN THE SOUTH AFRICAN CONTEXT

T.N. MUDAU

2021

THE USE AND IMPACT OF BUSINESS INTELLIGENCE (BI) SYSTEMS IN MANAGEMENT ACCOUNTING: AN EMPIRICAL STUDY IN THE SOUTH AFRICAN CONTEXT

BY

THANYANI NORMAN MUDAU
968384

A thesis submitted in fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY
(PHD)

Faculty of Commerce, Law and Management
University of Witwatersrand
Johannesburg

March 2021

Supervisors: Prof. Jason Cohen
Prof. Elmarie Papageorgiou

DECLARATION

I hereby declaring that this thesis is my work, unassisted work, except as acknowledged in the document.

The thesis is being submitted for the degree of Doctor of Philosophy (PhD) in the School of Accountancy at the University of the Witwatersrand, Johannesburg.

It was never submitted before for any degree or examination in this institution or any other University.

Signature ……………………………………………

TN Mudau

March 2021

ACKNOWLEDGEMENTS

The encouragement, guidance and support of the following people and reviewers is greatly appreciated.

I extend my sincerely appreciation to my supervisor, Professor Jason Cohen, for his leadership during the PhD journey from the inception to the thesis to the completion.

My co-supervisor, Professor Elmarie Papageorgiou, who had faith in me, provided guidance throughout the journey of the thesis, is greatly appreciated.

Ms Jennifer Croll for proofreading and editing the thesis.

Statistician, Chris Manyamba for assisting with the discussions of data analysis planning at the initial stage of analysing descriptive statistics.

My family, for the support they gave me during this long-term study. A special thanks goes to Sylvia, Ethel, Murangi, Mulweli, Phathu, Kayla, Norman, Jasmine.

My mom, Nyawasedza who encouraged me to further my studies so I can do my best to achieve more than expected in my career.

I extend my sincerely appreciation to academic experts, management accountants and finance executives who participated in the exploratory study and pre-tested the structured survey instruments developed and subsequently, participated in the pilot study.

I thank God for his strength, kindness and grace bestowed upon me to complete the study even when it looked impossible at the beginning.

ABSTRACT

Business Intelligence (BI) systems are used for gathering, managing, analysing, and sharing information about external and internal environments to gain insights for better decision making. Significant investments are being made in implementing Business Intelligence systems, but the extant evidence is limited as regards their impact on individual user performance and organisational performance. BI systems may have an especially important role to play in support of management accounting functions. This is because BI systems have the potential to assist management accountants to produce planning, costing, budgeting, forecasting and performance reports, and help them provide relevant and timely information to other managers, thus aiding their organisations to stay ahead of competitors. Yet, evidence suggests BI use may be low among management accountants who are often observed to perform their tasks outside of BI systems, such as maintaining their individual spreadsheets.

To address this problem, this study investigated the impact and use of BI systems at the individual level and organisational level, with a focus on the management accounting context. More specifically, this thesis examined the impact of innovative use of BI systems on the individual-level performance of management accountants and examined the extent to which organisational use of BI systems impacts a balanced set of performance measures, both directly and indirectly through impacts on the sophistication of management control systems.

To understand the factors affecting the use of BI systems and the impact of BI systems on individual performance, this thesis developed an extended DeLone and McLean (D&M) information system (IS) success model. The factors affecting use of BI systems included system quality, data quality, information quality and service quality. Use was conceptualised as both routine use (e.g., accessing standard reports, executing existing queries and running ad-hoc reports) and innovative use (e.g., using predictive analytics, self-service tools, constructing queries and visualizations). Task complexity was considered for possible moderating effects on the relationship between BI use and performance. The model was tested through a cross-sectional design using data collected from a sample (N=363) of management accountants, and through a longitudinal design using matched data from the management accountants collected over three time periods (waves) approximately 12 weeks apart. Structural equation modelling with AMOS was used for all model testing.

The individual level study confirmed that factors influencing the innovative use of BI systems by management accountants are system quality, data quality, information quality and service

quality, along with self-efficacy and task complexity. This study has also determined that routine use is less likely under conditions of task complexity and does not rely on self-efficacy to the same extent as innovative use. In addition, innovative use was found to be significant for individual performance by improving productivity and decision-making effectiveness. Furthermore, longitudinal results indicated that innovative use and user satisfaction are significant for individual performance at later time waves, improving productivity and decision-making effectiveness. Management accountants using only routine BI features were not found to enjoy improved performance. The thesis has thus contributed new insights into BI use among management accountants, confirmed the attributes of a BI system that promotes their use, confirmed the importance of distinguishing between routine and innovative use, confirmed that innovative use is especially important to user performance when task complexity is high, and that routine use is less likely to lead to productivity and decision effectiveness among management accountants. Moreover, the longitudinal design with tests of cross-lagged structural models over the three-time waves allowed the study to also confirm the causal ordering of variables within the IS success model, which prior research had not adequately established.

The thesis has also found that the adoption of BI systems into the operational functional areas of an organisation has an impact on organisational performance. The organisational impact was examined using the Balanced Scorecard (BSC) approach. The BSC defines a balance set of performance metrics including both financial and non-financial performance. This study also argued that an important intermediary performance outcome of BI systems is improved organisational Management Control Systems (MCS). MCS may help translate investments in BI into improved financial and non-financial performance outcomes. Data was collected using a survey of senior financial and other executives from 396 organisations drawn from a sample of Financial Mail (2016) top 200 companies and 196 public entities listed by National Treasury (PFMA, 1999). Model testing showed that BI systems can improve the non-financial performance of the organisation (customer performance, business process performance, and feedback and learning), as BI systems may turn data into actionable information. Furthermore, BI systems were found to directly improve the financial performance of organisations. This study thus provides sufficient evidence that adoption of BI systems is seen to improve the balanced set of performance measures. This is important for management to justify investments into BI systems within their organisations. The study also found that greater sophistication of MCS brought about by using BI systems impacts on organisational non-financial performance, particularly customer performance and business process, which then improve future financial performance. Feedback and learning performance was not found to have an impact on improvement of future financial performance in the sample.

This thesis has made a number of contributions. A theoretical contribution has been made by developing and testing an extended IS success model for BI systems in the management accounting context. The model includes factors such as data quality, distinguishes routine from innovative use, and incorporates consideration of task complexity. The work also brings new insights into the causal ordering of IS success constructs through analysis of cross-lagged models using data collected over three time-waves. This helped overcome limitations that arise when data is collected using only cross-sectional surveys, which lack temporal precedence. Theoretical contributions were also made by identifying measures of financial and non-financial performance that are relevant to understanding the impacts of BI at the organisational level, along with the role MCS plays in translating BI into performance outcomes. The thesis results will assist organisations on how to invest in and deploy BI systems, as well as the types of interventions that may be needed to extend individual users from routine use to achieve more innovative use of BI systems.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACCA	Association of Chartered Certified Accountants
AGFI	Adjusted Goodness of Fit Index
AVEs	Average Variance Extracted
BSC	Balanced Scorecard
BI	Business Intelligence
CB-SEM	Covariance Based Structural Equation Modelling
CEO	Chief Executive Officer
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CFO	Chief Financial Officer
CIO	Chief Information Officer
CIMA	Chartered Institute of Management Accountants
CR	Composite Reliability
CRM	Customer Relations Management
CSFs	Critical Success Factors
DF	Degree of Freedom
D&M IS	DeLone and McLean's Information System success model
DSS	Decision Support System
DW	Data Warehouse
EFA	Exploratory Factor Analysis
EIS	Executive Information Systems
ERP	Enterprise Resource Planning
ES	Executive Systems
ETL	Extract-Transform-Load
GFI	Goodness of Fit Index
ICT	Information Communication Technology
IFI	Incremental Fit Index
IT	Information Technology

IS	Information Systems
JSE	Johannesburg Stock Exchange
KMO	Kaiser Meyer Olkin
MCS	Management Control System
MIS	Management Information System
MLE	Maximum Likelihood Estimation
NFI	Normed Fit Index
OLAP	Online Analytical Processing
PCA	Principal Component Analyses
PFMA	Public Finance Management Act
RFI	Relative Fit Index
RMSEA	Root Mean Square of Error Approximation
SA	South Africa
SAICA	South African Institute of Chartered Accountants
SAP	System Application
SEM	Structural Equation Model
TLI	Tucker-Lewis Index
X^2	Chi-Square

CHAPTER 1: INTRODUCTION TO THE PROBLEM OF BUSINESS INTELLIGENCE (BI) USE AND MANAGEMENT ACCOUNTING PERFORMANCE

1.1 The Potential of Business Intelligence (BI)

Business Intelligence (BI) is a management innovation focused on developing processes and systems to collect, transform, cleanse, and consolidate organisational data for the purposes of improving individual decision making (Mircea and Andreescu, 2009). BI systems were popularised in the early 1990s due to the increases in the volume of structured and unstructured data available within organisations. The term BI was coined in 1989 by Howard Dressner (Gartner Group Analyst) to represent a new set of technologies that overcome previous approaches to Information Technology (IT) enabled decision support such as "Executive Information Systems (EIS), Decision Support Systems (DSS), Management Information System (MIS) and Online Analytical Processing (OLAP)" (Watson and Wixom, 2007; Arnott, Lizama and Song, 2017). BI systems were introduced to handle organisational challenges, such as overflow of data, lack of information, lack of knowledge, lack of analytical capability and insufficient management reports (Lin, Tsai, Shiang, Kuo and Tsai, 2009; Ain, Vaia, DeLone and Waheed, 2019). BI systems rely on underlying transactional data available within the organisation (Petrini and Pozzebon, 2009; Abusweilem and Abualoush, 2019). The underlying transactional data includes internal transactional data from operational systems such as Enterprise Resources Planning (ERP) systems as well as customer information from Customer Relations Management systems (CRM). This data is usually stored in an accessible data warehouse (Noor, Giovanni and DeLone, 2019). The consolidated data is manipulated to produce valuable information for presentation on users' desks as reports or displayed on screen such as dashboards or scorecards (Olszak and Ziemba, 2012; Gartner, 2012). Purported benefits of better-quality information from BI systems include cost and time savings, better decisions, improved business processes, and support for the accomplishment of operational and strategic objectives (Wixom and Watson, 2010; Dawson and Van Belle, 2013). Ultimately, the use of BI systems should assist an organisation to stay ahead of its competitors (Lin et al., 2009).

1.2 Management Information System and Business Intelligence System

Olszak and Ziemba (2012) argued that traditional decision support and management information systems are unable to adequately assist users and decision makers. Specifically, they are limited in helping managers make decisions under time pressure, monitor competition, examine different views of the organisation simultaneously, carry out constant analyses of numerous data or consider different variants of organisation performance. In addition, existing MIS do not have the capacity to integrate data from decentralised (i.e., internal, and external) information system sources that include both financial and non-financial data. The interpretation of data from these various information systems cannot be done in broad contexts effectively and they are not capable of identifying new data interdependencies (Abusweilem and Abualoush, 2019). In order for the organisations to gain competitive advantage in the market there is a need for an information system that will allow the organisation to perform scenario planning and analyse the impact of various scenarios on the organisation and its environment (Skyrius, Kazakevičienė and Bujauskas, 2013).

BI systems provide a solution to these data integration, timely decision making and scenario planning challenges that MIS cannot handle. Thus, BI systems can be defined as the development of processes and systems that collect, transform, cleanse, and consolidate organisational data in an accessible store for the presentation on user's desks as reports or analysis (Olszak and Ziemba, 2012). Petrini and Pozzebon (2012) define BI systems as the ways an organisation can explore access and analyse information in the data warehouse to inform and develop insights that lead to improved decisions (Petrini and Pozzebon, 2012). "BI systems capabilities include intelligent exploration, integration, aggregation, and a multidimensional analysis of data originating from various information resources" (Petrini and Pozzebon, 2009; Negash, 2004). In this thesis, BI systems are thus defined as information systems software that is used for the purpose of gathering, managing, analysing, and sharing information about external and internal environments to gain insights for better decision making. Wierder and Ossimitz (2015) argued that "BI systems combine data from internal information systems of an organisation, and they integrate data coming from the particular environment e.g., statistics, financial and investment portals and miscellaneous databases" (Farzaneh et al., 2018). Such software has a potential of providing adequate and reliable up-to-date information on different aspects of enterprise activities (Wierder and Ossimitz, 2015; Farzaneh et al., 2018).

1.3 Individual Use and Impact of BI Systems

Users of BI systems include individual managers who require more complete, accurate and timely information to make operational and strategic decisions about customers, financials, internal business processes, and the learning and development aspects of the organisation (Petrini and Pozzebon, 2009).

Although the implementation of BI systems has started to have an impact on individual users and organisational outcomes (Wierder and Ossimitz, 2015), Wixom and Watson (2010) have argued that the benefits of implementing BI systems are not always fully realised. They argue that the realization of benefits depends on the manner and extent to which individuals use the available BI systems. Hajri, Xu, Nuwangi and Seder (2014) further argued that to realize benefits from a system, an organisation should encourage individual system users to move beyond basic or *routine* use and towards more *innovative* use. Routine use occurs when users use BI systems to extract pre-built reports only, but without using the more analytical features of BI systems. Innovative use occurs when users are able to use more advanced BI system features, such as self-service tools, interactive visualization, predictive analytics and drill down functionality to support their work and improve their individual performance (Li, Hsieh and Rai, 2013). Without innovative use, organisations are unlikely to benefit fully from their organisational information base to achieve *inter alia* costs savings and improved business processes. However, the factors affecting more innovative use of IT systems, including BI systems, are little understood (Gonzales and Wareham, 2019). This research gap that exists must be addressed because, without this knowledge, organisations are not in a strong position to manage the realization of the investments made in implementing their BI systems (Hajri et al., 2014).

Only a few studies (Hou, 2012; Popovič, Hackney, Coelho and Jaklič, 2012; Montero, 2019; Gaardboe, Nyvang and Sandalgaard, 2017) have investigated factors that influence the individual usage of BI systems. However, these studies have not distinguished between routine use and innovative use of BI systems and a need exists for additional research that examines the factors influencing the innovative use of BI systems by individual decision makers within organisational settings (Hou, 2018; Mudzana and Maharaj, 2017). One specific management function that may benefit from innovative BI system use is management accounting (Rikhardsson and Yigitbasioglu, 2018; Rom and Rohde, 2006). Use of BI systems has been recognised as assisting management accountants to produce planning, costing, internal reports, external reports, budgeting, forecasting and performance information (Rom and Rohde, 2006), improve the quality and speed of their decision making (Bhimani, Horngren, Datar and Foster, 2008), and help them provide relevant and timely information to other managers and aid their organisation to stay ahead of competitors (Tomic, 2006). Although BI systems have been marketed as an intelligence tool to support management accounting, management accountants are observed as continuing to perform their work on stand-alone systems like Excel, and management accounting functions typically continue to be performed outside of BI systems (Vakalfotis, Ballantine and Wall, 2011; Rikhardsson and Yigitbasioglu, 2018). Understanding why there may be varying use of BI systems in the management accounting context, and whether the use of BI systems can provide value to the management accounting function, is thus a research problem in need of investigation.

DeLone and McLean's (1992) Information System Success Model (D&M) has been extensively used to explain factors influencing system usage at an individual level. The D&M IS success model identifies information quality, system quality, service quality, and user satisfaction as important factors that influence Information Systems (IS) system use at the individual level (DeLone and McLean, 1992, 2003). Despite the D&M success model being extensively used to validate the factors that influence IS system use; it has not been sufficiently tested whether the model's factors explain innovative use as compared to routine use. It remains a question as to whether it is a relevant theoretical lens through which to examine the innovative use of BI systems by management accountants. Moreover, individual level factors such as the user's computer experience, level of training, and self-efficacy for innovative use may interact with the D&M IS success model factors to influence the degree of innovative use of a BI system (Schierder and Gluchowski, 2011; Gonzales and Wareham, 2019).

Studies drawing on the D&M IS success model to explain individual-level use and performance have been conducted in nursing, education, and marketing environments where individual users are not IT professionals but domain users (e.g., Cohen, Coleman and Kangethe, 2016; Courtois et al., 2014; Chen, 2010; Chen and Cheng, 2009; Gaardboe et al., 2017; Angelina, Hermawan, and Suroso, 2019). Therefore, the D&M IS success model may also be relevant in the management accounting context where individual management accountants represent the domain or community of users of BI systems (e.g., Tomic, 2006; Hou, 2012; Nadia, 2014), with BI systems often developed for management accountants.

Prior literature has also revealed that there is limited understanding of the impacts of BI systems on management accountants (Rikhardsson and Yigitbasioglu, 2018; Elbashir et al., 2021; Vakalfotis et al., 2011; Venter and Tustin, 2009). Thus, in addition to examining the determinants of innovative use, the consequences of innovative use for user performance needs to be understood. The innovative use of BI systems is expected to impact individual user performance along indicators that include decision making quality, job performance, productivity, decision speed and effectiveness (Hou, 2012; Hou, 2018). Yet, there is a need to empirically validate such purported impacts of BI systems use on individual decision making and performance (Popovič et al., 2012). In doing so, it may also be necessary to consider whether the complexity of the tasks and decisions facing the individual user influences the degree to which the use of BI systems impact on that individual's performance. Thus, by examining both the determinants and consequences of BI systems use, BI systems can be better designed and managed to meet the end-user's expectations, facilitate more complex decision-making tasks, and improve their decision-making performance (Popovič et al., 2012).

1.4 Organisational Use and Impact of BI Systems

In addition to research on the use and impact of BI systems on individuals, research on the impacts of BI systems on *organisational performance* is still surfacing (Hart and Snaddon, 2014; Lönnqvist and Pirttimäki, 2006; Gorla, Somers and Wong, 2010; Arnott, 2008). Much of the literatures on BI systems and organisational performance focuses on financial performance only and ignores other intermediary and non-financial performance measures (Lönnqvist and Pirttimäki, 2006). Examining the impact of BI systems on a more *balanced* set of organisational performance measures will assist an organisation in justifying the decision made to invest in BI systems (Somers and Wong, 2010; Božič and Dimovski, 2020). The organisational performance impacts of BI systems may thus be more than an aggregate of individual benefits. A focus on financial and non-financial performance measurement could provide organisations an opportunity to better understand the ways in which BI systems can influence performance (Aydiner et al., 2019).

Furthermore, in the context of management accounting, one intermediary performance outcome of significance is the performance of the Management Control System (MCS). MCS is a process in which managers ensure that resources are obtained, allocated and used in accomplishing organisational objectives (Chenhall, 2006; Narayanan and Boyce, 2019). The adoption of BI systems may have an incremental impact over existing MCS, and result in greater sophistication of MCS (Nadia, 2014). BI systems may improve MCS by supporting planning and forecasting capabilities to assist organisations in setting organisational objectives and assessing if organisational resources are being allocated correctly towards achieving organisational objectives (Hart and Snaddon, 2014; Gorla et al., 2010). Furthermore, BI systems can provide performance information on MCS (i.e., budget, variance analyse and performance reports) to all levels of employees within the organisation, and this may influence the behaviour of employees to implement organisational strategies. In a BI system environment, the performance of MCS may improve as information becomes more easily available and management spends more of their time analysing performance than manipulating data (Somers and Wong, 2010). A better MCS in turn, should result in improved business performance on outcomes, such as profitability, planning and budgets (Malmi and Brown, 2008).

In today's environment, business continues to change, which means that technology systems are often incompatible with current needs and management accountants spend significant amounts of time reworking their MCS data on spreadsheets (ACCA, 2012). Given the need to improve organisational performance through MCS, empirical evidence of the impact of BI systems on the sophistication of MCS within organisations and on higher-order organisational performance measures is needed. Moreover, the impact of BI systems on performance may be contingent on certain factors such as the organisation's size, culture, environment, quality of the board and structure (Martin, 2020). For example, in larger organisations, or those operating in more complex competitive environments, there may be a greater need for BI systems to support more timely decision making, more variables to consider in decision making and more data to collate (Liew, 2019). Studying the effects of such contingencies on the link between BI systems and organisational performance is needed. The research problem and objectives of the study are further outlined in the next section.

1.5 The Research Problem

The study investigates two main problems.

The *first problem* of the study is to investigate the factors influencing the innovative use of BI systems by individuals in the management accounting context. There is also a need to further investigate the impact of innovative use of BI systems on management accountants' individual performance. Although past IS research (Hou, 2012; Popovič, Hackney, Coelho and Jaklič, 2012; Hajri et al., 2014) has revealed factors influencing the individual usage of IS systems, those studies did not distinguish between routine and innovative use or were not carried out in the BI system context. Understanding factors influencing the innovative use of BI systems remains a research problem in need of investigation (Hou, 2012).

Some studies (Wixom and Watson, 2010; Hou, 2012; Popovič et al., 2012; Montero, 2019) found a positive relationship between IS usage and individual user performance while other studies (e.g., Jain and Kanungo, 2005; Gorla, Somers and Wong, 2010; Gaardboe et al., 2017; Angelina et al., 2019) found that IS systems usage has no impact on individual user performance. Because of these varied results, the relationship between use and performance needs to be better understood. Addressing the question whether innovative use as opposed to routine use is necessary for individual user performance may provide an explanation for discrepancies in past findings. The management accounting context provides a particularly interesting setting within which to investigate this question. This is because, although investments in BI systems are often made with the aim of supporting management accounting functions, management accountants continue to work with organisational information and data outside of BI systems where they often prefer to process data in their individual spreadsheet systems (Granlund, 2011; Appelbaum et al., 2017).

The *second problem* to be investigated is whether BI systems have an impact on organisational outcomes – including the sophistication of MCS and a balanced set of organisational performance measures. Organisational performance is a set of financial and non-financial performance indicators (Neely, Gregory and Platts, 2005; Božič and Dimovski, 2019). Prior studies investigating the impact of BI systems on organisational performance were focused on evaluating performance as financial performance, such as profitability (e.g., return on assets, net profit, sales turnover, and assets turnover) but ignored non-financial performance (O'Brien and Kok, 2006; William and Williams, 2007; Narayanan and Boyce, 2019). The sole focus on financial performance does not provide a balanced view of organisational performance. Financial performance is only one aspect in a more balanced view of performance measurement (Lönnqvist and Pirttimäki, 2006). Other prior studies (Elbashir, Collier and Davern, 2008; Elbashir and Williams, 2007; Božič and Dimovski, 2020; Aydiner et al., 2019; Gauzelin and Bentz, 2017) that examined the impacts of BI systems on non-financial performance only focused on internal business process improvement and ignored other aspects, such as organisational learning and development, and customer satisfaction. Consequently, the role of BI systems in improving financial and non-financial organisational performance requires further attention. Examining this relationship will aid management in justifying the decisions that they have made in investing in BI systems.

This study also argues that an important intermediary performance outcome of BI systems is an improved organisational Management Control System (MCS). MCS (formal and informal controls) is concerned with the allocation, monitoring and coordination of organisational resources in order to assist managers in achieving organisational objectives (Granlund, 2011). The impact of using BI systems to support MCS is lacking. Malmi and Brown (2008) theorised that the use of IS systems has resulted in a sophistication of MCS, but others have theorised that the use of IS systems had no impact on MCS (Vakalfotis et al., 2011; Grabski, Leech and Schmidt, 2011; Kallunki, Laitinen and Silvola, 2011). Consequently, the relationship between organisational BI systems use and the sophistication of MCS is not well understood and the changes brought by BI systems on MCS require further attention (Popovič et al., 2018; Vallurupalli and Bose, 2018; Narayanan and Boyce, 2019; Abusweilem and Abualoush, 2019). Greater sophistication of MCS brought through the use of BI systems may in turn, impact on organisational financial and non-financial performance (Kallunki et al., 2011; Quattrone and Hopper, 2005; Elbashir et al., 2013; Elbashir et al., 2011; Rom and Rohde, 2006).
Prior studies (Chenhall, 2006; Chapman and Kihn, 2009; Elbashir et al., 2013) that provided a link between MCS and organisational performance have however produced mixed results. Consequently, it has been argued that the role of contingency factors such as organisational strategy, size, environment, structure, quality of board and culture be considered for their effects on the relationships between organisational use of BI systems, MCS and organisational performance.

The research objectives are outlined in Section 1.6.

1.6 The Research Objectives

Given the research problems discussed above, this study has three objectives:
RO1. To identify and empirically examine factors explaining the observed variation in the innovative use of BI systems by individual management accountants.
RO2. To examine the impact of innovative use of BI systems on the individual-level performance of management accountants.
RO3. To examine the extent to which organisational use of BI systems impacts on a balanced set of organisational performance measures, both directly and indirectly, through impacts on the sophistication of management control systems.

To achieve these objectives, the study addresses the following three research questions.

RQ1. What are the factors influencing the extent of innovative use of BI system among management accountants?
RQ2. What is the impact of innovative use of BI system on the individual performance of management accountants?
RQ3. To what extent is the organisational use of BI systems' impacts on a balanced set of organisational performance measures, both directly and indirectly, through impacts on the sophistication of management control systems?

The study extends the D&M IS model to address RQ1 and RQ2 and explain the variation of IS systems usage and the individual impacts of IS systems use (DeLone and McLean, 1992, 2003). To extend the D&M IS model, Burton-Jones and Straub's (2006) perspectives on IS usage along with Hajri et al.'s (2014) work into innovative use of IS systems have been drawn upon. RQ1 and RQ2 are addressed in Chapter 3, Chapter 6, and Chapter 7.

RQ3 was addressed by drawing *inter alia* on the Balanced Scorecard (BSC) performance measurement system (Kaplan and Norton, 1992). The BSC considers both financial and non-financial performance. The MCS factors will also be included in addressing RQ3 (Chenhall, 2003). MCS includes both formal and informal controls that management use to assist managers in executing organisational strategies. The RQ3 has been addressed in Chapter 4 and Chapter 8. The outline of this study is mapped according to the proposed chapters (Figure 1).

1.7 Contribution of the Study

This study aims to make an original contribution in four ways, namely theoretical, contextual, methodological, and practical.

First, a theoretical contribution is made by drawing on and extending the D&M IS success model to develop a BI systems success model focused on innovative use. The construct of innovative use has not been sufficiently explored. Moreover, the model has been extended by including factors reflecting individual user characteristics. By testing the model, the study determines the utility of the underlying theories in explaining innovative use of BI systems and establishing innovative use as a prerequisite for individual user performance. Furthermore, the study distinguishes between routine and innovative use, and examines the role of task complexity in the links between use and user performance. Further, the longitudinal design integrates use, user satisfaction and individual performance from the theoretical framework of the D&M model to develop a dynamic BI system success model.

Further theoretical contributions are made by hypothesizing the impact of BI adoption at the organisational level on financial and non-performance using the BSC approach. The constructs of non-financial and financial performance in a BI systems environment has not been sufficiently explored. The testing of the model explains the impact that BI systems have at the organisational level on financial and non-financial performance. A further contribution is made by including the sophistication of MCS as an intermediary outcome linking BI with organisational performance. The role of BI systems in improving MCS outcomes is not sufficiently theorized in the literature. The study also considers the potential impact of organisation size, strategy, technology, structure, culture, and environment on the links between BI systems and MCS and organisational performance. The testing of the model thus contributes to the development of theory that explains the mechanisms through which BI systems influence organisational performance and extends our understanding of the organisational conditions under which BI systems usage is most important to performance.

Second, the study makes a contextual contribution by examining BI systems use at both the individual and organisational levels in the context of management accountants from the South African context. The study makes an extensive contribution to the field of accounting information systems through evaluating whether BI systems have impacted the sophistication of MCS in the organisation. The sophistication on formal and informal controls has been evaluated to provide guidelines to management accountants and business executives on how to deploy and use BI in an MCS environment to enhance controls within the organisation. Management accounts are known to rely on their own spreadsheet tools and the relevance of BI systems to the performance of management accountants has not been sufficiently explored until this study.

Third, the study makes a methodological contribution by operationalization of the measures of innovative use, routine use, organisational performance, and data quality that is informed by the literature as well as an initial round of interviews with BI system users. This has resulted in an improved operationalization of the extended D&M IS success model. The BSC approach adopted for the organisational level study resulted into the development of a balanced performance measurement of BI systems from the organisational point of view. Moreover, as a methodological contribution, the thesis explains how longitudinal design and structural equation modelling can be combined to improve analysis of implied causal linkages in the IS success model. Specifically, the use of the cross-lagged SEM design in this work can help researchers better understand the causal relationships between use, user satisfaction and individual performance outcomes as theorized in the D&M IS success model.

Fourth, the results of this study can assist organisations to improve decisions on how they invest in and deploy BI systems, as well as the types of interventions that may be needed to achieve innovative use by individuals. For example, the balanced performance measurement approach will assist organisations with concrete indicators that can be used in measuring the benefits and success of their BI systems. Further, by identifying the determinants of innovative use and the relative influence of innovative over routine use, organisations will be better positioned to implement necessary interventions to promote innovative use of BI among their management accountants and develop strategies for migrating these users from other systems.

1.8 Structure of the Study

The thesis structure is as follows. This thesis has seven chapters which includes, Chapter 1, that has introduced the problem of BI system use and impacts, Chapter 2 reviews the literature on BI systems, Chapter 3 details the conceptual development of the research models used to study individual use and impacts of BI. Chapter 4 details the conceptual development of the research model used to study organisational use and impacts of BI. Chapter 5 discusses the research methodology and design followed in conducting the research. Chapter 6 presents result of a cross-sectional study on individual use and impacts of BI systems to answer RQ1 and RQ2. Chapter 7 relies on longitudinal data collected over three time-waves to test a cross-lagged model to establish causal relationships in the individual use and impacts of BI, further extending RQ2. Chapter 8 tests the model of BI system use at an organisational level using the BSC approach. Finally, Chapter 9 concludes the study. Table 1 indicates the number of potential articles to be published from the thesis.

Table 1 Articles to be Published

Chapter	Status
6	Mudau, T. N., Cohen, J. & Papageorgiou, E. 2021. Determinants and Consequences of the Routine and Advanced use of Business Intelligence (BI) Systems by Management Accountants, under review.
7	Mudau, T.N., Cohen, J. & Papageorgiou, E. 2021. Testing Causal Relationships Between Use and Individual Performance: A Cross-Lagged Structural Equation Model, Working Paper.
6	Mudau, T.N., Cohen, J. & Papageorgiou, E. 2021. The role of Task complexity in the relationship between system Use and individual Performance, Working Paper.
8	Mudau, T.N., Cohen, J. & Papageorgiou, E. 2021. Organisational Performance Outcomes of the Use of Business Intelligence (BI) Systems and The Importance of Management Control Systems, Working Paper.

.

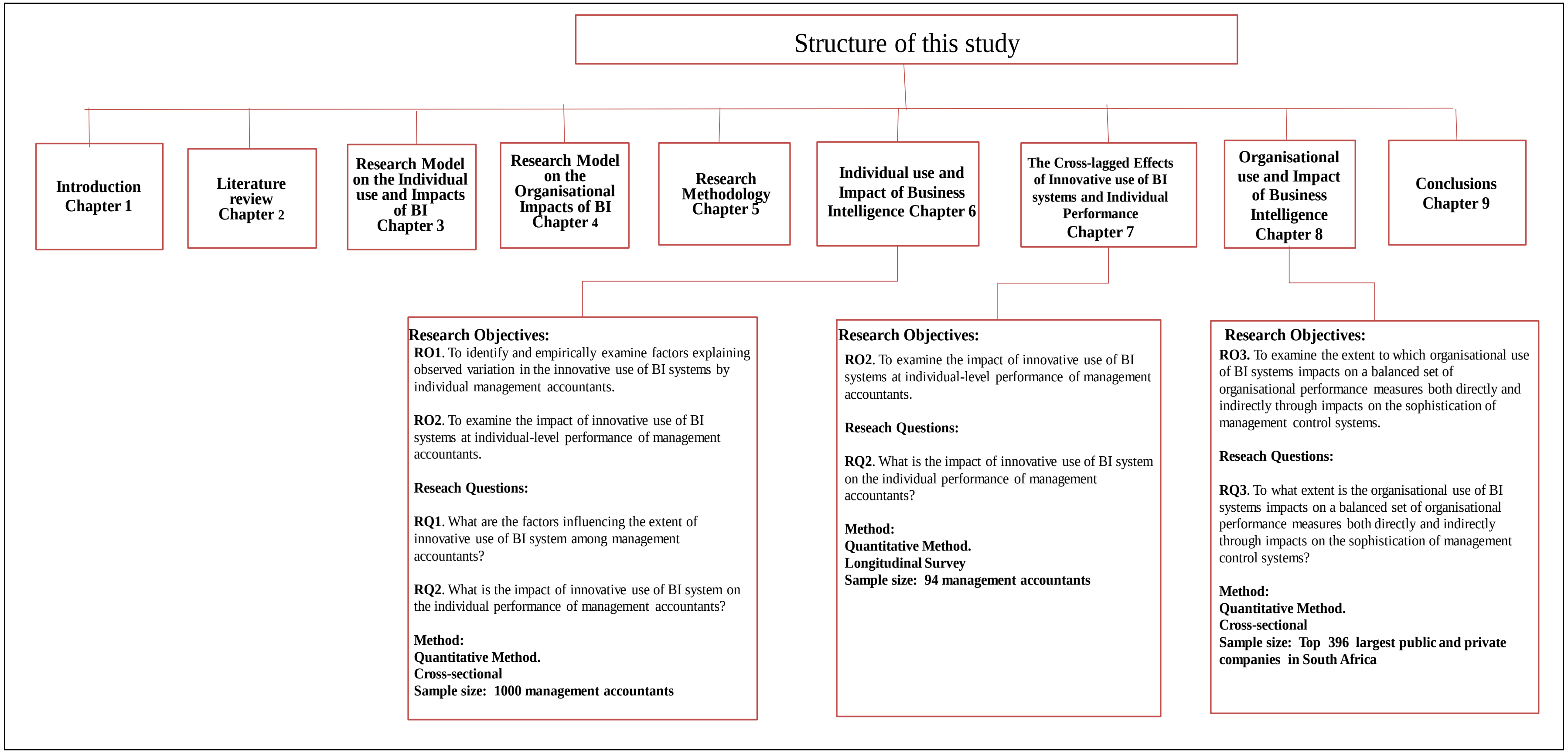


Figure 1 Study Outline and Objectives Mapped to Thesis Chapters

The structure of thesis has been outlined in figure 1. The next chapter presents the literature review on BI system use.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

In Chapter 1, the research topic and problem were introduced. This chapter reviews the existing literature relevant to the current study. First, the process followed to carry out the review is presented. Next, business intelligence and BI systems are defined and described. Thereafter, the evolution, attributes and benefits of BI systems is discussed in detail. The literature review then focuses attention on the shortcomings of existing literature on the use and impact of BI systems. The chapter highlights the potential role of BI systems in management accounting and explores its potential impacts on management control systems and the balanced scorecard.

2.2 Approach to the Literature Review

In preparing the literature review, several sources were used which included the Google Scholar search engine, Science Direct, EBSCOhost, Emerald, and other online academic databases. To carry out the review, search phrases were developed using the following key terms: use, impacts, job satisfaction, performance, Balanced Scorecard, DeLone and McLean, Business Intelligence, Information system use and continuance, information system success model.

Identified studies were included if they were available in full text, in English, were from peer reviewed journals, addressed the topics of "BI system" or "information system" or adoption" or "innovative" or "routine" or "use" or "individual" or "organisational" or "performance" or "management accounting" or "decision making" or "user" or "satisfaction". The search was further restricted to empirical studies using survey, experiment, field study, correlation.

As suggested by Webster and Watson (2002), a structured approach was used, similar to what would be used in a systematic review to gather articles for the purposes of presenting a narrative review that is concept centric. The approach to searching articles was aimed to be exhaustive and comprehensive and that was guided by quality considerations in selecting sources for inclusion in the review (Pare et al., 2015).

2.3 The Business Intelligence (BI) System

In recent years, many organisations have been overwhelmed with the amount of internal and external data available at their disposal (Petrini and Pozzebon, 2012; Arnott, Lizama and Song, 2017; Hou, 2018). In handling the amount of data, many systems have been created as per individual business user requirements, which over time, has resulted in various isolated and disparate data management systems. The obvious lack of integration between these decentralised systems has impeded business knowledge and motivated the need for improved Business Intelligence (BI) solutions (Ramanathan et al., 2017). BI systems provide for such intelligence by extracting data from various systems and integrating the information for reporting purposes and decision making (Olszak and Ziemba, 2012). The BI terminology was popularised by Howard Dressner in 1989 as a new set of technologies that was developed to supplement the shortcomings of decision support, such as "Executive Information Systems (EIS)", "Decision Support Systems (DSS)", "Management Information System (MIS) and Online Analytical Processing (OLAP)" (Watson and Wixom, 2007; Farzaneh et al., 2018). BI systems were popularised in the early 1990s due to the increases in the volume of structured and unstructured data available within organisations (Arnott, Lizama and Song, 2017).

There have been various definitions of BI systems and there is no commonly acceptable definition of BI systems thus far. The term BI system commonly describes the ideas and methods used to improve organisational decision-making by using data and information collected from an underlining portfolio of information systems (Pirttimäki, Lönnqvist and Karjaluoto, 2006; Sun et al., 2018).

BI systems have also been defined from two dimensions, namely the management dimension and technical dimension (Petrini and Pozzebon, 2012; Lautenbach, Johnston and Adeniran-Ogundipe, 2017). The management dimension is focused on the role of BI in gathering data from various sources and analysing it to provide meaningful information, while the technical dimension is focused on technological tools and processes used to develop BI.

Lönnqvist and Pirttimäki (2006) argued that BI systems should be seen as more than just an enabling technology. BI is a management innovation focused on developing processes and systems to collect, transform, cleanse, and consolidate organisational data for the purposes of improving individual decision making (Mircea and Andreescu, 2009; Farzaneh et al., 2018). BI systems are thus a set of integrated tools, technologies, software, users, and procedures used to collect, integrate, analyse, and make information available for decision making; they capture, access, analyse and convert data into information that can be used to improve organisational performance. Popovič et al. (2012) expand on the objectives of BI systems, which are to explain, plan, predict and solve problems, and to improve organisational knowledge and decision-making processes to achieve organisational goals.

Closely related to the concept of BI is the data warehouse. A data warehouse is used to store data from various systems within the organisation so the data can then be used to support decision making (Olszak and Ziemba, 2006; Lautenbach et al., 2017). BI systems access and analyse data in the data warehouse to develop insights, inform and improve decisions (Petrini and Pozzebon, 2012; Sun et al., 2018).

BI systems are often compared with EIS, DSS and MIS as all of them share a common focus on decision making and information management (O'Brien and Kok, 2006; Farzaneh et al., 2018).

However, Negash (2004) argued that BI systems are more than simple replacements of EIS, DSS and MIS. They are a new technology which bring an increased capability due to the maturity and sophistication of the programming and analytical capability of BI. Olszak and Ziemba (2012) argued that traditional decision support and management information systems are no longer able to adequately assist users and decision makers in making decisions under time pressure, monitoring competition, simultaneously examining different views of the organisation, and carrying out constant analyses of numerous data to consider different variants of organisation performance. In addition, existing MIS do not have the capacity to integrate data from decentralised (i.e., internal, and external) information system sources that include both financial and non-financial data (Lautenbach et al., 2017). Section 2.4 expands on the evolution of BI systems.

Taken together, BI system can be summarised as technologies, applications and processes used to collect, analyse, access and store data about the organisation's external and internal environment so that it can be used by individuals to gain insights and make informed decisions (Wixom and Watson, 2010; Popovič, 2017). BI systems combine available data from various systems available within the organisations with data from external environment which include but not limited to statistics, financial and investment portals and other useful databases (Wierder and Ossimitz, 2015). Such software systems are meant to "provide adequate and reliable up-to-date information on different aspects of enterprise activities" (Wierder and Ossimitz, 2015). BI systems are capable of consolidating data from various organisational systems and provide one single view. This integrated data is what allows BI systems to be most informative to management and useful for decision making (Wixom and Watson, 2010; Abusweilem and Abualoush, 2019).

2.4 Evolution of BI Systems

New demands and pressure on organisations have compelled them to search for technology that will assist in gathering, analysing, and processing large volumes of data from different sources to serve as one source of knowledge to be used to make strategic decisions. BI systems were developed to address the limitations of four earlier information and decision tools utilised within organisations.

First, Management Information Systems (MIS) emerged in mid 1960s and have been at the core of supporting organisation with their various reporting tasks. MIS are designed to extract data from underlying databases to provide information required for the operational manager to monitor and control business processes with the aim of projecting future performance. MIS are used to produce scheduled reports (i.e., daily, monthly, quarterly, weekly, half yearly and yearly) by middle management levels (Olszak and Ziemba, 2012; Popovič, 2017), for decisions and feedback on daily operations. Olszak and Ziemba (2003) argued that MIS have not readily met decision makers' expectations, such as for real time decision making, analysing information from different angles and monitoring competitors.

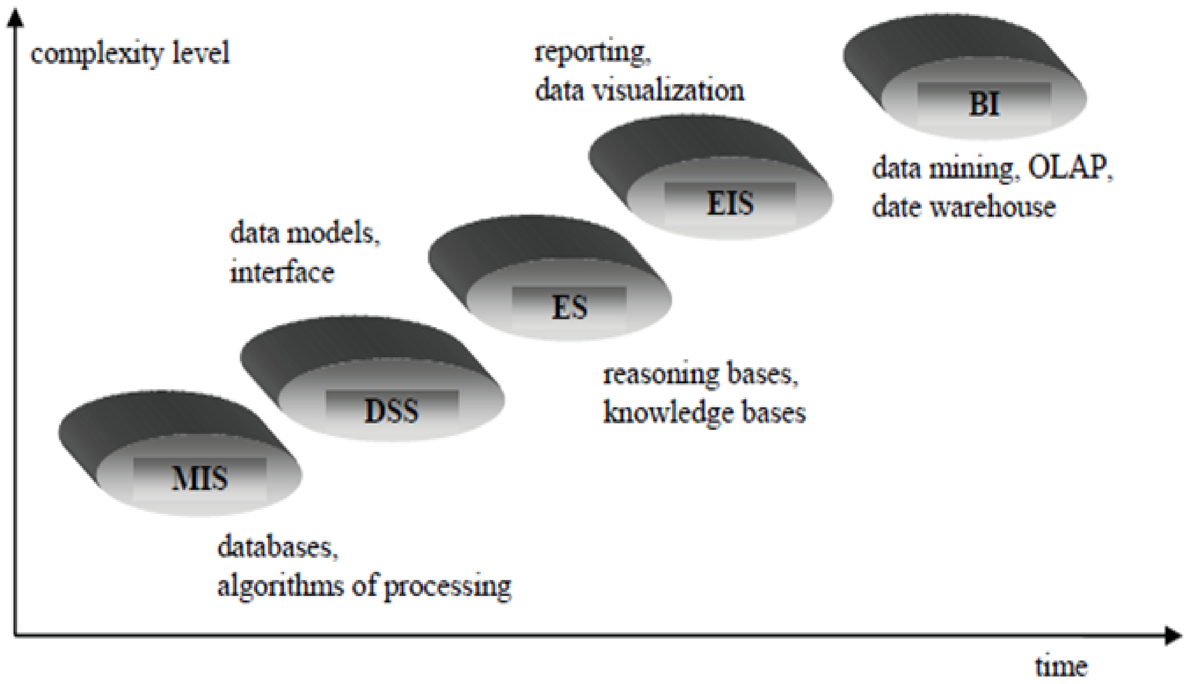
Following MIS and in an effort to overcome their limitations, Decision Support Systems (DSS) emerged as computer software to support *ad hoc* analysis to help top management with decision making for emerging problems not specified in advance (Drake and Martin, 2020). Unlike the MIS, the DSS helps top level managers in making unstructured or semi-structured decision problems. The DSS are thus flexible and adaptable to the user's decision-making approach and changes in the environment and offer the ability draw a query report from a specified database. The DSS are more interactive systems than the MIS and thus assist top managers to convert raw data and documents into useful information to identify and solve problems and take decisions (Kopáčková and Škrobáčková, 2006).

Expert Systems (ES) subsequently emerged as technologies to emulate human expert decision making ability, with the objective of solving difficult problems presented (Kopáčková and Škrobáčková, 2006). Tan (2017) stated that the ES features allow for knowledge storing, knowledge reasoning and interpretation. The interpreter should be able to interpret the information processed and confirm correctness (Tan, 2017).

Executive Information Systems (EIS) were a further class of information system designed to support executive management with information relevant for making strategic level decisions

(Papageorgiou and Bruyn, 2010). Unlike MIS and DSS which were focused on operational and tactical decisions, EIS focused on making access to information easier for planning activities (Arnott, 2007). EIS brought improvements to reporting, such as visualisation. Data visualisations provide information in graphic format for easier use and communication. However, EIS were often not flexible and were expensive to maintain (Williams and Williams, 2007). This then necessitate the introduction of the new technologies, such as the BI system. Figure 2 describes the evolution of BI systems.

Figure 2 Evolution of the BI Information System



(Source: Olszak, and Ziemba, 2004)

Although MIS, DSS, ES and EIS are important tools, they have not been seen to meet decision maker expectations for (Olszak and Ziemba, 2012):

- supporting decision making under pressure;
- monitoring competition;
- acquiring data to present different points of view of the organisation;
- carrying out constant, real-time, analyses of large volumes of data; and
- considering different variants or dimensions of organisational performance.

Moreover, these traditional information systems cannot easily integrate data being housed across various systems within the organisation. In addition, existing MIS do not have the capacity to integrate data from decentralised (i.e., internal, and external) information system sources that includes both financial and non-financial data (Olszak and Ziemba, 2012). The interpretation of data from these various information systems cannot be done in broad contexts effectively and they are not capable of identifying new data interdependencies. These earlier systems (MIS, DSS, ES and EIS) lack proper tools that support data integration, analysis, discovery, and advanced visualisation (Power, 2007; Abusweilem and Abualoush, 2019).

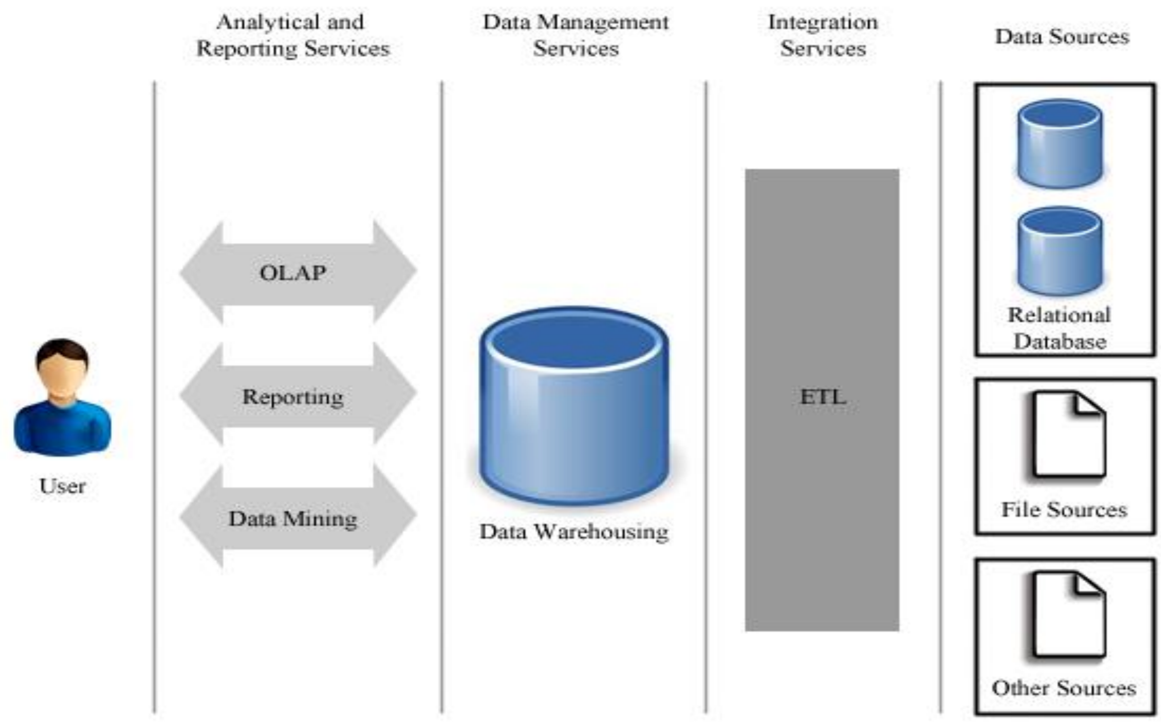
In order for organisations to gain competitive advantage in their market, there is a need for information systems that allow them to perform scenario planning and predictive analytics and analyse impacts on the organisation and its environment (Skyrius et al., 2013; Farzaneh et al., 2018).

BI systems address these needs and overcome the limitations of earlier information and reporting tools (Lin et al., 2009).

2.5 Attributes of BI Systems

A BI system is made of various inter-related components (Hočevar and Jaklič, 2010). These components allow users to abstract and analyse information in a format that is easy to read and understand. There are four components of a BI system, namely, analytics and reporting component, a data management services component, a data integration component, and the data sources component (Muhammad et al., 2014). These four components of the BI architectures are depicted in Figure 3. Although others, e.g., Ponniah (2010), have categorised only three components of BI systems as data acquisition (i.e., data sources), data storage (i.e., data management services) and information delivery (i.e., analytics and reporting), the importance of integration, such as using Extract-Transform-Load (ETL) tools, should not be underemphasised (Noor et al., 2019). The four components are discussed next.

Figure 3 Business Intelligence Architecture



(Source: Muhammad et al., 2014)

The first and second components of BI system are data source and Extract-Transform-Load (ETL). Data sources are the raw data from various internal and external data stores. The data staging and sourcing is an area where all data are stored in preparation of loading the data into the data warehouse (Hočevar and Jaklič, 2010; Farzaneh et al., 2018). The data that is extracted is both transactional data and master data and can be loaded from sources that are both structured and unstructured. The data is cleansed and transformed before it can be transferred to the data warehouse. In this integration stage, data obtained from the various sources is extracted into the BI using ETL tooling. Once the data has been transformed into a format required by the structure of the data warehouse, the integrated data can then be stored in the data warehouse (Muhammad et al., 2014; Farzaneh et al., 2018).

The third component is the Data Warehouse (DW). DW is an information environment that stores all data extracted from various system into one platform (Muhammad et al., 2014). The DW is not a transactional environment but it is used for warehousing purposes so that data can then be used by the BI system to perform analytics for decision making (Hočevar and Jaklič, 2010). The DW thus provides an integrated and consistent view of the organisational data and ensures that historic data and current data is available to users for their decision making

(Skyrius et al., 2013; Abusweilem and Abualoush, 2019). Through the use of a DW, BI systems thus support decision making without interfering with the existing operational systems, such as ERP systems.

The fourth component is the BI system's analytics and reporting service. This component makes accessing information in the DW easier and provides the data analysis required for decision making (Hočevar and Jaklič, 2010). Information is often made available through a reporting framework and/or interactive dashboards that can be used by management in an organisation. Users receive information and can analyse business performance in a variety of ways. One type of analytics is predictive in nature and aims to project what will happen in future (Olszak and Ziemba, 2006; Abusweilem and Abualoush, 2019). For example, the analytics service component assists management in performing modelling, such as on the future performance of a particular product or service where the impact of external shocks, such as drought on volume of water sold, can be modelled. Management can then take the necessary steps to improve the bottom-line of the organisation using predictive analytics. As another example, multidimensional analysis can be performed using Online Analytical Processing (OLAP) (Olszak and Ziemba, 2003). OLAP draws data from the DW and is used for data discovery. It is regarded as one of the most powerful tools of BI and has the capability of limitless report viewing, complex analytics and predictive modelling, including 'what if' scenarios (Olszak and Ziemba, 2012; Noor et al., 2019). A third example, of the analytics and reporting service component of the BI system is the use of data mining technology where large volumes of data in the DW are processed to provide meaningful patterns and trends. For example, organisations can have insight on trends with customers allowing them to take necessary steps to increase sales volumes and decrease costs (Ponniah, 2010).

Of the four components, the analytics and reporting component is the most relevant to this study. Information is the heart of the BI system project and reporting and analytical capabilities provide users with necessary insights into their organisations (Gartner, 2015). The various reporting and analytic features of typical BI systems are summarised in Table 2. Users, including management accountants, make varying use of these features to support their decision tasks.

Table 2 Business Intelligence

Information Delivery	
Reporting	The capability allows for the development of distributable interactive reports that are formatted according to the organisational needs. The reports should be flexible enough to accommodate the reporting cycle that includes financial, operational and performance information (Gartner, 2012).
Dashboards	The dashboards provide a graphic representation of the selected performance indicators, they are "intuitive interactive displays of information", "including dials", "gauges", "sliders", "check boxes and traffic lights" (Gartner, 2012).
Ad hoc query	The capability allows the user to create their own report using data available on DW without being assisted by any IT technician (Gartner, 2012).
Search-based BI	A 'Google-like' search index that allows for a search on "both structured and unstructured data sources and puts results into a classification structure of dimensions and measures that users can then navigate" (Noor et al., 2019).
Analysis	
Online analytical processing (OLAP)	The technology allows the user to analyze large volumes of data that involve complex relationships. OLAP uses "graphical user interface and processing procedures to produce a visual result in different forms to the users" (Azita, 2011).
Interactive visualization	The capability allows the user to display data in an efficient way by using "interactive pictures and charts instead of rows and columns".
Predictive modelling and data mining	The capability allows for the use of known data to build a data model that can be used to predict future outcomes. The analysis of the historic data gives an opportunity to forecast based on probabilities of events such as financial, economic,

	customer behavior and market risks (Gartner, 2012; Chen and Lin, 2021).
Scorecards	The capability takes key performance indicators and displays them on the dashboard, the key performance indicators are aligned with the strategic objectives of the organisation (Kubina, Koman and Kubina, 2015). The scorecard should be linked to detailed reports and information to allow further analysis.

(Source: Gartner, 2012)

Based on the above discussed attributes of a BI system, the BI system is evidently not a transactional tool but a system of components that extract information from other transactional systems such as ERP systems. The BI system tools include OLAP, data mining, ETL, DW, analytics and reporting. The BI system is used to collect and transform data into meaningful information that can be displayed through interactive dashboards, visualisations, and scorecards for use in decision making within organisations (Jaklič, Grublješič and Popovič, 2018). BI systems cannot be compared with transactional systems as the transactional systems are the data sources of the BI system (Nofal and Yusuf, 2013). BI system stores large volume of data from various transactional systems and provide for a single view of data (Nofal and Yusuf, 2013; Muhammad et al., 2014).

2.6 The Benefits of BI Systems

This section provides an overview of the benefits of BI systems. This assists in justifying the significance of the research. Organisations implementing BI systems expect to realise the benefits after the implementation of the system. The benefits of the BI system justify why companies are rushing to implement BI systems in large numbers. However, there has been an estimated implementation failure ranging between 50% to 80% worldwide (Nofal and Yusuf, 2013; Beal, 2005; Legodi and Barry, 2010).

To realize the benefits of the BI system, it is important to develop a coherent BI strategy that will ensure that pitfalls are avoided (Laguir et al., 2019), although there is no consensus on the complete list of the benefits of the BI system. Below are some of the benefits of the BI system obtained from the literature review.

A BI system's return on investment can be evaluated in two ways namely: (1) improved efficiency in information distribution, and (2) the availability of information that may result in improvement of decision making (O'Brien and Kok, 2006; Popovič, 2017). The first approach can be measured easily, and it has small returns as compared with improved decision making. Decision making improvement offers greater returns as there is an opportunity *inter alia* of preventing wasted organisational resources from poor decisions, missed opportunities due to lack of information, along with allowing more immediate operational responses such as redefining business processes to cope with new ways of doing business (Olszak and Ziemba, 2012; Noor et al., 2019). The BI system has a potential of cutting the time to prepare reports and reduce the personnel required to prepare reports. The personnel can then be re-deployed to other areas where they can add value. Jaklič et al. (2018) stated that benefits of the BI system can only be achieved if the system is used efficiently and it is fulfilling the purpose for which it was implemented.

Kubina et al. (2015) also argued that BI systems can offer several benefits to organisations. BI systems can end the "guess work" within an organisation as information is readily available for decision making. The consolidation of all data into one BI platform through DW improves communication amongst various divisions when co-ordinating work activities. This enables organisations to respond quicker on financial issues, customer demand changes and supply chain operations. The use of BI systems has the potential for improving all aspects of business (Nofal and Yusuf, 2013). This is because information is regarded as the most precious asset a company can have in its disposal. Decisions that are made timeously and accurately have greater potential for improving organisational performance (Jaklič et al., 2018). Organisations may gain competitive advantage as BI systems can fast-track quick decision making, as acting quickly and correctly allows managers to respond to market changes and improve performance. In addition, BI systems can improve customer satisfaction as information about customer queries and experiences is made available in a timely manner, which allows organisations to solve customer queries faster (Azita, 2011; Popovič, 2017).

Olszak and Ziemba (2003) categorised the benefits of BI system into three decision making levels and argue that BI systems can support decision making at all organisational levels, namely Strategic level, Tactical level, and Operational level.

The strategic level uses BI systems to enable the formulation of specific objectives and to ensure follow-up on achieving the set strategic objectives. Several comparative reports can be generated e.g., on profitability of a particular product or effectiveness of distribution channels, and predictive analytics and future forecasting can take specific assumptions on senior managers into account (Olszak and Ziemba, 2003). An organisation's success and sustainability is dependent on how organisations are able to adapt to changes in customer demand. For this purpose, BI systems can gather information about market patterns, which can then be used to innovate new products or services in anticipation of changes in customer demands (Ranjan, 2009; Ameen et al., 2020). As another example of a strategic level benefit, BI can be used to obtain information about competitors from market research and inform management on steps that competitors are taking, so that management can take informed decisions to stay ahead (Gartner, 2012).

At the tactical level, BI systems may provide decision making support for areas such as finance, sales, marketing, operations, and treasury management. The system is used for optimisation of future actions and modifying financial and technological aspects of organisation performance to aid the organisations in achieving their strategic objectives more efficiently and effectively (Gibson, Arnot and Jagielska. 2004).

At the operational level, BI systems can be used to perform *ad hoc* analyses and answer a question on whether a department's on-going operations are up to date with financial standing, sales, customer, and co-operation with suppliers (Olszak and Ziemba, 2003).

Furthermore, and as an additional way of understanding BI benefit, Hsu (2004), Olszak and Ziemba (2003), Olszak and Ziemba (2006) and Gartner (2015) outlined how BI systems can support data analyses and decision making in various areas of corporate management, customer relations, monitoring of business activities, planning and decision support, such as the following:

- Analysing financial performance that requires reviewing of costs, revenues, income statement comparisons, balance sheet and liquidity, financial market performance, complex controlling, and identification of potential irregularities and fraud;
- Analysing marketing performance that includes receipts, sale profitability, gross profit margin, sales targets, number of orders, time taken to order, actions taken by competitors, running promotional campaigns;
- Analysing customer performance which includes customer profitability, along with modelling the behaviour of customers and customer satisfaction;

- Analysing production performance that includes monitoring production bottlenecks, delays in producing orders, compares production produced by plants;
- Analysing logistic to identify possible supply chain partners quickly;
- Analysing wage data that includes returns to labour, wage components with reference to type, payroll charges, contributions, and average wages; and
- Analysing employee personal data that includes employment turnover, employment types, employee personal data, etc.

There is a sense that organisations and decision makers can benefit from the implementation of BI systems, however measuring these benefits is a bigger challenge than measuring the costs (Lönnqvist and Pirttimäki, 2006). Implementing BI systems appears to affect non-financial and intangible benefits such as quality improvements and timely information. Although there is an expectation that such non-financial benefits will result in improvement in financial performance (i.e., cost savings or revenue growth), there is always a time lag that exists between information provided by the BI system and the financial gain expected. It is therefore difficult to measure the benefits derived from the implementation of BI systems in practice (Lönnqvist and Pirttimäki, 2006; Hočevar and Jaklič, 2010).

Furthermore, BI systems have been viewed as contributing to the quality of customer relationship management, customer satisfaction and creating new market opportunities (Ameen et al., 2020). It is difficult to measure these improvements with a specific financial value (Hsu, 2004). "The bigger question to be asked is how much a satisfied customer is worth compared with one who is less satisfied (Ameen et al., 2020)? Can the increase in sales in a particular market segment be attributed to using a BI system or it would have naturally happened in any case (Lönnqvist and Pirttimäki, 2006)? Is a report produced by a general manager valuable or is it more beneficial for the report to be produced by someone else so that managers are free to focus on other strategic matters" (Hsu, 2004)? These questions raised a challenge particularly when looking at the benefits of the BI system. The use of BI systems to drive benefits remains a problematic field that needs to be understood (Hsu, 2004; Lönnqvist and Pirttimäki, 2006; Ameen et al., 2020).

Since it is difficult to understand the benefits of adopting BI systems within organisations, Lönnqvist and Pirttimäki (2006) proposed that the BI system should be viewed from the Balanced Scorecard (BSC) perspective. The BSC approach suggests that the ability to reach organisational objectives should be measured according to the four perspectives (Kaplan and Norton, 1992, 1993, 1996, 2001, 2006).

- financial (financial resources meet the mission of the organisation);
- customer (customers perceive the organisation positively);
- internal processes (business process are designed to support the mission of the organisation); and
- learning and growth (knowledge is available to achieve the organisational mission).

These benefits can only be derived if the users within the organisations are using the BI system. However, there is variation in the degree to which BI systems are used by decision makers as well as variation in the nature of use of these systems. Those who are using the system extensively are likely to enjoy more benefits than those using only more basic functions. It is difficult to separate the benefits from the use of the system, as the way in which the individual employees are using the system can influence the realisation of benefits.

This section identifies the benefits of the BI system. However, the newness of the BI system and the fact that it differs with the traditional system has resulted in reports of failures. This necessitates a need for research into factors that might promote the use and successful implementation of BI systems. The next section discussed the shortcomings of the BI system.

2.7 The Shortcomings of BI Systems

Although, there are many benefits or advantages of using BI systems, shortcomings also exist. The shortcomings of BI system are summarised as follows.

- Poor data quality - The BI system is dependent on accuracy and completeness of data. Failure to address data quality will affect the quality of the BI system and consequently, decisions that depend on that data. Organisations should embark on a detailed exercise to cleanse data before the BI system can be used. Data management policies should be in place to regulate the parameters that data should meet before migration or integration can happen (Olszak and Ziemba, 2006; Giustia, et al., 2019).
- Poor use - Although BI systems are being implemented, the usage of BI is still low and its complete functionality in reporting and analytics services is often not fully utilised. Users may find it easier to use only basic features of BI systems without looking at the

advanced functionality. Like any technology in the beginning, there are few users of BI systems as people are still comfortable with their more familiar legacy systems. If the usage problem is not resolved, then BI benefits might never be fully realised (Olszak and Ziemba, 2003).

- Costs - BI systems are normally expensive to implement, and small to medium organisations might find it difficult to implement these systems due to budget constraints. The use and maintenance of such systems may not be feasible to implement. Before the implementation of the system, it is important for organisations to conduct cost benefit analyses so that the implementation can be justified (Pirttimäki et al., 2006).
- Complexity - The implementation of the system is complex as this technology should extract data from various systems internally and externally. If the configurations are not managed appropriately, organisations may not get the required information for decision making (Giustia, et al., 2019).
- Historic data - The reason of implementing the BI system is to accumulate historic data so that data can be used by management for meaningful decision making. Historic data may no longer be relevant as markets are constantly changing (Gibson et al., 2004).
- Resistance to change - Change management is the key in ensuring that users buy into using the new technology. If change management is not managed properly, there might be resistance from users refusing to use the system or continuing with their previous methods for managing data and reporting. This happens when the value of the project is not communicated amongst the strategic users. Change agents must be properly constituted so that resistance to change can be avoided (Hočevar and Jaklič, 2010).
- Failure to manage expectations - Users might expect that they can obtain all types of reports and analytics simply by a click of a button from the BI system. If BI systems provide fewer reports that expected or if users find accessing information more difficult than initially anticipated, then users can become despondent and lose confidence in the usefulness of the BI system (Lönnqvist and Pirttimäki, 2006).
- Budget over-runs - BI systems require large budgets. If the implementation plan is not managed properly, it may lead to budget over-runs. The implementation might not be completed as expected, the project might be abandoned, or the system may fail to be fully implemented, leading to a waste of resources (Pirttimäki et al., 2006).

Taken together, these possible shortcomings highlight that problems with data quality can affect use, users may have concerns about system usability, they may feel information is not always useful to their decisions and may not be sufficiently supported to manage change and transition to a new system. Because BI systems offer a great deal of reporting and analytics functionality, variations in use are likely to be widespread. Benefits can be limited if users rely solely on simple reports and do not take advantage of features such as predictive analytics and dashboards. Eventually, organisations may find it difficult to justify continued investments in BI, especially if the expected market, customer, financial and other benefits do not easily materialise. There is a long causal chain linking BI to better decision making and improvement in organisational outcomes.

2.8 Management Accounting and BI Systems

Management accounting is concerned with providing “financial and non-financial information” to management for decision making (Bhimani et al., 2008), and helping them provide relevant and timely information to other managers. The success of a business organisation is dependent on how it can rely on information provided by management accounting. The information is used by decision makers inside and outside the organisation for planning, decision making and control. Data used by management accountants must be stored in databases and supported by relevant information systems (Bringnall and Ballantine, 2004; Abdusalomova, 2019). Information systems have been the cornerstone of management accounting practice since the 1970s (Granlund and Mouritsen, 2003). Management accounting was one of the first areas in which IS technology was implemented (Uppatumwichian, 2013), where IS could assist management accountants with data collection, data analysis, and information presentation.

More recently, business intelligence systems have been introduced to support management accounting. Management accountants who want to achieve high quality information and useful reports are turning to the use of BI systems (Hadid and Al-Sayed, 2021; Rikhardsson and Yigitbasioglu, 2018). The data warehouses that underpin BI are helping to address poor data quality issues that can impede management accounting (Bringnall and Ballantine, 2004). Furthermore, BI system’s analytical and reporting services such as On-Line Analytical Processing (OLAP) and intelligent agents can be used by management accountants to explore, search, and analyse data stored in the data warehouses (Tomic, 2006; Malmi et al., 2020). BI systems have been recognised as assisting management accountants to produce planning, costing, internal reports, external reports, budgeting, forecasting and performance information (Rom and Rohde, 2006), improving the quality and speed of managerial decision making

(Bhimani et al., 2008; Rikhardsson and Yigitbasioglu, 2018; Sutton, 2006), and helping their organisation to stay ahead of competitors (Tomic, 2006).

Yet there is still limited understanding on how BI systems are used to support the management accounting function (Rom and Rhode, 2006). For example, despite the potential of BI systems, management accountants are known to be continuing to perform their work on stand-alone systems and use spreadsheet software, such as Excel, to support their data management and reporting work. It is not known whether BI systems are failing to be implemented to support management accountants or if they are choosing to work around BI systems due to challenges experienced in use. Regardless, management accounting functions continue to be performed outside of BI systems (Vakalfotis, Ballantine and Wall, 2011). Moreover, in the instances where BI systems are used in management accounting, it is not evident whether, and to what extent, BI systems are impacting management accounting processes or work outcomes (Uppatumwichian, 2013; Appelbaum et al., 2017).

Previous studies (Adam and Pomerol, 2008; Elbashir et al., 2011; Granlund and Mouritsen, 2003; Uppatumwichian, 2013) that looked at BI system and management accounting, found that there is no guarantee that the deployment of BI systems can support management accounting. This is purely because not all management accountants continue with the use of the BI system after implementation. It is not fully understood whether the non-use of the BI system is because of frustration and dissatisfaction. Elbashir et al. (2011) argued that the implementation of the BI system has resulted in the work of management accountants becoming complex. The complexity is brought about by the fact that information outputs of the system are not as easy to use as anticipated. In addition, functions such as budgeting, forecasting, performance reporting and costing are not easily migrated to BI systems (Rom and Rhode, 2006). The way in which the system is being used may also be a challenge, as some management accountants may use only the basic features of the BI system while others may opt to experiment with using advanced features. The variation in use may determine the realisation of benefits, satisfaction with and continued usage of the system (Sanchez-Rodriguez and Spraakman, 2012). It is also reported that management accountants often use BI systems as a database only, and do not develop dashboards or make use of other tools to provide information to management for decision making (Grabski et al., 2011). Consequently, the way the BI system is used can play a critical role in deriving benefits. Understanding the use of BI systems in the management accounting context, and the value such use can provide to the management accounting function, is thus a research problem in need of investigation (Arnott, 2008).

2.9 Management Control System

A Management Control System (MCS) was initially defined by Anthony (1965) as the mechanism by which management ensures resources are allocated efficiently and effectively in accomplishing organisational objectives. From this definition, MCS was largely seen as a set of accounting-based controls for planning, monitoring, and performance measurement and, importantly, emphasised the separation of management control from strategic control and operational control. Later, Simons (1987) explained MCS as the combination of formal and informal routines and procedures that managers carry out to execute related organisational activities. ThusMCS has come to be seen as a combination of of controls that aid managers in achieving organisational objectives while executing their work (Chenhall, 2006), and the 'whole lot' that managers can do to help their organisations to realise their strategies and plans (Merchant and Van der Stede, 2007). Over the years, MCS has also evolved from focusing on formal quantifiable information to assist management in decision making to include a broader scope of information (Bedford, Malmi and Sandelin, 2016). This incorporates external information such as information about customers, competitors, and markets, along with non-financial information such as on production processes and information on a broad spectrum of decisions and informal personal and social controls (Bedford et al., 2016). Taken together, MCS is seen as an active tool that empowers employees in executing their work to achieve the set organisational objectives and goals.

Chenhall (2006) stated that MCS controls can be categorised as formal controls and informal controls. Formal controls include but are not necessarily limited to budgets, key performance measurement, strategic planning, activity-based management, product costing and reporting (Tucker and Parker, 2014). These are more visible controls that exists and are often easier to study from a research perspective. Empirical studies of MCS have focused mainly on formal controls and ignored informal controls. Informal controls are not intentionally designed (Tucker and Parker, 2014). Informal control includes cultural and administrative controls relating to informal systems influencing organisational members and are based on mechanisms encouraging self-regulation (Otley, 1980; Chenhall, 2006; Chenhall, 2003; Smith, 2007). They include undocumented organisational policies often derived from the organisational culture. Cultural controls include clan controls that are influenced by organisational shared values and norms (Smith, 2007). While administrative controls the behavior on the employees in various ways. This includes how organisational structures and hierarchy are designed ad how employees are related within the organisations, along with governance, and policies and procedures (Granlund, 2011). In addition, administrative controls can also be influenced by existing policies and procedures (Malmi and Brown, 2008). For example, the formal organisational mission or objectives may reflect the values and beliefs of the dominant culture. Informal controls are important aspects of the control system as the effectiveness of formal controls is dependent on the nature of the informal controls that are in place (Chenhall, 2003).

The main objective of MCS is to ensure that employees are aligned and behave in a consistent manner in achieving the organisation's objectives as outlined in the strategic plan. Improper implementation of the MCS may lead to risks such as financial loss, reputational damage, and even possible organisational failures (Appelbaum et al., 2017). In order to have a high probability of success organisations must implement good and sound MCS. Organisations that fail to maintain good MCS or fail to implement one are likely to have negative consequences. Carenys (2012) stated that the important issue about MCS is not about the type of controls developed and implemented but rather how the controls are used. The way in which these controls are used could be the differentiating factor between organisations that design and implemented MCS (Sandelin, 2008).

In this thesis, MCS is thus viewed as a combination of formal and informal controls put in place to encourage employees to behave in line with organisational goals and motivate them to improve their performance and achieve organisational objectives. Malmi and Brown (2008) stated that MCS cannot be studied in isolation. It is important to study MCS as a package, as different controls affect each other. This view was supported by Sandelin (2008) who argue that studying formal controls alone without taking the effects of informal controls can lead to inaccurate conclusions being drawn of their effects. Studying MCS as a package can lead to a better understanding of its effects on organisational outcomes (Elbashir et al., 2021). Therefore, MCS is expected to influence the broad behaviours of employee, which in turn assist in achieving organisational objectives.

The introduction of IS such as BI systems is expected to influence MCS within organisations (Nielsen, 2018; Peters, Wieder and Sutton, 2018). BI systems are increasingly seen as technologies that can transform management control processes and extend the sophistication of MCS resulting in improved information and improved organisation performance (Arnold, 2018; Rikhardsson and Yigitbasioglu, 2018). The sophistication of MCS is enabled through better analytical reporting available on BI systems to provide real time information on budgeting, key performance indicators, activity-based management, product costing and scorecard measures. In addition, predictive analytics provide the capability of predicting the behaviour of product performance in the future based on current information available (Nespeca and Chiucchi, 2018). Thus, leading researchers to theorise that the use of IS systems should result in a sophistication of MCS (Malmi and Brown, 2008). However, others are less convinced that the use of IS systems has had an impact on MCS (Vakalfotis et al., 2011; Grabski, Leech and Schmidt, 2011; Kallunki, Laitinen and Silvola, 2011). Consequently, the relationship between organisational BI systems use and the sophistication of MCS is not well understood and the changes brought by BI systems on MCS require further attention (Vakalfotis et al., 2011). This is important because if greater sophistication of MCS could be brought through the use of BI systems, this may in turn impact on organisational financial and non-financial performance (Kallunki et al., 2011; Quattrone and Hopper, 2005; Elbashir et al., 2013; Elbashir et al., 2011; Rom and Rohde, 2006).

Emerging research has begun to address this question. For example, Elbashir et al (2021) examined the extent to which BI systems enabled integrated MCS and whether the assimilation led to improvement of business process and organisational performance. They found BI enabled MCS did lead to improvement in business processes and enhancement in organisational performance. However, their study did not differentiate between informal and formal MCS. This thesis seeks to study MCS as a package by considering both formal and informal controls. Furthermore, their focus was only on business processes and not on other organisational performance measures such as learning and development and customer performance outcomes. For example, the adoption of BI systems may help organisations in understanding customer profiles better, re-engineering internal business processes based on operational performance measures, and providing feedback and learning on employees' skills in the organisation. This might in turn, improve MCS such as strategic planning and budget processes in the organisation. Furthermore, once management understands what their customers are buying, they can use this information to formulate their strategic objectives and set realistic targets (Elbashir et al., 2021). In addition, BI systems improve visibility of internal processes and make it possible to identify areas in need of improvement, which can be used to refine strategy on a continuous basis (Kallunki et al., 2011; Owusu, 2017). BI systems may also make the monitoring of plans against actual performance easier as the required information can be displayed on a BI dashboard (Granlund, 2011). BI systems may support informal control by providing information to all employees that will encourage a culture of performance and the motivation to implement the strategy of the organisation (Elbashir et al., 2021). The monitoring of organisational performance may help align all the employees to work towards a common goal (Chapman and Kihn, 2009). More importantly, BI allow detailed monitoring of cost allocated to the product per cost driver and allow for cost reduction while improving profitability of the organisation. Hence, it is important to link BI systems to both formal and informal MCS to better understand the impact that BI has on the sophistication of MCS.

2.10 Balanced Scorecard

The Balanced Scorecard (BSC) was introduced by Kaplan and Norton (1992) after realising the financial measures alone are not sufficient for evaluating organisational performance. The traditional financial performance measures only focused on historic outcome, BSC was introduced to include indicators that can predict future financial performance of the organisations (Kaplan and McMillan, 2021). The BSC has become a useful managerial tool that can help organisations to translate their strategy into actionable initiatives and projects. This helps organisations with the planning, execution, control and monitoring of organisational strategy (Kaplan and Norton, 1996). It is an important management tool that can be used to assist top management on the right decision making taken to achieve the desired outcome. Within BCS, the corporate plan gets translated to vision, information and intelligence (Kaplan and Norton, 2001).

The BSC framework measures performance by looking at four different organisational perspectives that included financial, customer, internal business process performance and learning and development performance (Kaplan and Norton, 2006). The financial measures are used by top management to evaluate the organisation’s financial position in the market (Božič and Dimovski, 2020). While customer performances are used to measure the image of the organisation in the market (Owusu, 2017). Internal business process performances are used to measure whether the business processes designed are addressing customers and shareholders expectations (Kaplan and Norton, 2006). Learning and development are used to measure the organisational commitment in achieving long term strategy in terms of human resources development and innovation point of view (Alnoukari and Hananao, 2017). The pillar in building cooperate capacity emanates from knowledge management (Quesado, Guzmán and Rodrigues, 2017). The effectiveness of the BSC approach in practice is, however, dependent on the information and technologies that organisations are using to support them in implementing a BSC (Davis and Albright, 2004). Because BI systems are able to handle complex data from various systems, they may be an especially useful IS tool to support the BSC approach (Alnoukari and Hananao, 2017). This is because BI systems are expected to provide timely and efficient information that can be projected for management to monitor and improve both financial and non-financial performance (Vallurupalli and Bose, 2018). The introduction of BI systems is thus expected to impact on both the financial and non-financial dimensions of organisational performance (Elbashir et al., 2021). According to Jaklic et al. (2009), IS, such as BI systems, have indeed started to have an impact on the *balanced set of organisational performance measures* (Chapman and Kihn, 2009; Popovič et al., 2018; Vallurupalli and Bose, 2018).

Organisations with BI systems are better positioned to address customer queries and defects speedily as information can be made more rapidly available to management for decision making than in organisations without BI systems (Petrini and Pozzebon, 2009; Peters et al., 2016). Therefore, organisations with BI systems have real-time information available on customer queries and defects about products or services offered. Without monitoring customer queries and defects, organisations cannot make the type of decisions required to achieve full customer satisfaction and improve those processes which impact on performance (Cox, 2010; Aydiner et al., 2019). In addition, BI systems can assist organisations in monitoring the launching of the new products, create more value for customers and improve operational efficiencies and these are used to evaluate the learning and growth perspective in the organisations (Kallunki et al., 2011; Božič and Dimovski, 2019). A BI system also allows for monitoring of marketing campaigns, so resources can then be allocated to the performing campaign to improve product visibility in the market. Employee development areas can be identified, and the necessary training and development can then be arranged (Hart and Snaddon, 2014; Gauzelin and Bentz, 2017). The BI systems have a potential of cutting the time to prepare reports and reduce the personnel required to prepare reports. The personnel can then be re-deployed to other areas where they can add value (Kubina et al, 2015). BI systems can thus provide a more complete picture that assists management in evaluating the elements of non-financial performance and making better decisions, which result in improvement of non-financial performance.

Prior studies investigating the impact of BI systems on organisational performance were focused on evaluating performance as financial performance, such as profitability (e.g., return on assets, net profit, sales turnover, and assets turnover) but ignored non-financial performance (O'Brien and Kok, 2006; William and Williams, 2007; Narayanan and Boyce, 2019). The sole focus on financial performance does not provide a balanced view of organisational performance. Financial performance is only one aspect in a more balanced view of performance measurement (Lönnqvist and Pirttimäki, 2006). Other prior studies (Elbashir et al., 2008; Elbashir and Williams, 2007; Božič and Dimovski, 2020; Aydiner et al., 2019; Gauzelin and Bentz, 2017) that examined the impacts of BI systems on non-financial performance only focused on internal business process improvement and ignored other aspects, such as organisational learning and development, and customer satisfaction. Consequently, the role of BI systems in improving financial and non-financial organisational performance requires further attention. Examining this relationship will aid management in justifying the decisions that they have made in investing in BI systems.

2.11 Conclusion

This chapter introduced BI systems and their components, discussed the evolution of BI systems from earlier management information and decision support systems and identified some use cases for BI systems in support of operational, tactical, and strategic decision making. The potential benefits of BI systems were deliberated along with various challenges and shortcomings. The review highlighted that the realisation of benefits is likely to be dependent on BI system use and that benefits are often difficult to quantify. In addition, the chapter presented a discussion on the use of BI systems, specifically in the "Management Accounting context". There is a limited understanding of BI system use among management accountants. It is important to understand how individual management accountants interact with the BI system. Furthermore, the complexity of management accountants' task may encourage the type of use and their satisfaction with the system. The use of the system may enhance management accounting functions and their individual performance. Furthermore, the chapter presented a discussion on MCS and how the introduction of BI systems may result in sophistication of formal and informal MCS. Finally, the BSC was discussed as a combination of financial and non-financial performance. BI systems havepotential impact on both financial and non-financial information, however previous research on BI focused mainly on financial performance and ignored non-financial performance such as learning and development and customers. The impact of MCS as an intermediary between BI system use and organisational performance is also not fully understood.

The literature review has thus helped motivate for the importance of this research study in helping organisations to justify their investments in BI systems. The study also establishes factors affecting the use of the BI systems and its impact on individual users in the Management Accounting context.

The next chapter develops the conceptual model and the hypothesis to be tested.

CHAPTER 3: RESEARCH MODEL ON THE INDIVIDUAL USE AND IMPACTS OF BI SYSTEMS

3.1 Introduction

In chapter 2, the literature review relevant to the study was discussed. Prior literature revealed that there is limited understanding of how BI systems are used to support the management accounting function and how BI use impacts management accountants (Rom and Rohde, 2006; Vakalfotis et al., 2011; Venter and Tustin, 2009; Tomic, 2006; Nadia, 2014). This chapter addresses research objectives (RO1 and RO2) which are to identify and empirically examine factors explaining observed variation in the routine and innovative use of BI systems and the impact of use on individual-level performance of management accountants. In addition to examining the determinants of innovative use, it is especially important to examine the consequences of innovative use for user performance. The innovative use of BI systems is expected to impact individual user performance along indicators that include decision making quality, job performance, productivity, decision speed and effectiveness (Hou, 2012). By examining both the determinants and consequences of BI systems use, BI systems can be better designed and managed to meet the end-user's expectations, facilitate more complex decision-making tasks, and improve their decision-making performance (Popovič et al., 2012). In the next section of this Chapter, the D&M model is introduced and explained in detail as the theoretical underpinning for the research model. The constructs of routine use, innovative use, task complexity and data quality, which extend the D&M model, are then discussed. Finally, the research model is developed with the hypothesis to be tested.

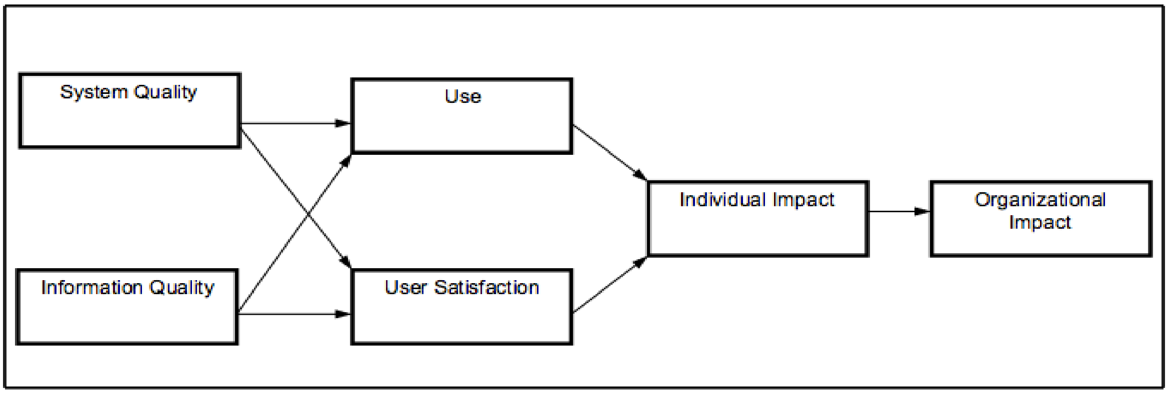
3.2 DeLone and McLean IS Success Model

The DeLone and McLean (D&M) information system (IS) success model provides the framework used in this study. The D&M model has been used to understand the attributes of an IS system that are relevant to its individual users and which lead to user satisfaction, use and performance outcomes (Cohen, Coleman and Kangethe, 2016). According to the D&M model, variables such as system quality, information quality and service quality are important attributes to individual user's evaluation of the system. The use of D&M IS success model has been supported (Wang, Wang and Shee, 2007; Chen, 2010; Ain et al., 2019; Hou, 2018), and found useful in the past studies of individual users (Wu and Wang, 2006; Hou, 2012; Schmiedel, Vom Brocke and Recker, 2014). However, it has not yet been adequately adapted to underpin research into BI systems. This work therefore contributes by adapting and extending the D&M IS success model to develop the study's research model and hypotheses through which research questions (RQ1 and RQ2) are addressed.

Studies drawing on the D&M IS success model to explain individual-level use and performance have been conducted in nursing, education, and marketing environments where individual users are not IT professionals but domain users (e.g., Cohen, Coleman and Kangethe, 2016; Courtois et al., 2014; Chen, 2010; Chen and Cheng, 2009; Gaardboe et al., 2017). Therefore D&M IS success model may also be relevant in the management accounting context where individual management accountants represent the domain or community of users of BI systems (e.g., Tomic, 2006; Hou, 2012; Nadia, 2014; Ain et al., 2019), with BI systems often developed for management accountants.

The D&M IS Success Model provides linkages between the attributes of an IS systems and the individual use of that system, on the one hand, and the subsequent benefits derived from that use of the IS on the other hand (DeLone and McLean, 1992; Wang et al., 2007; Wu and Wang, 2006; Chen, 2010; Aldholay et al., 2018). The original model was developed by DeLone and McLean (1992) emanating from the review of 180 prior studies on IS success. The original D&M IS success model has six dimensions as illustrated in Figure 4. DeLone and McLean (1992) proposed that the following dimensions are important contributors of the IS success model, information quality, system quality, system use, user satisfaction, individual impact, and organisational impact. The D&M IS success model thus indicates that IS success can be understood as the satisfaction of individual users with the IS, their use of the IS, the impact that the system has on these individual users which in turn, benefits the organisation (Wang et al., 2007; Montero, 2019). Use and satisfaction are achieved through the system's qualities, most notably its system quality and information quality. These constitute the independent variables in the model and are the basis for the influence of the system on individuals using the system (Chen and Lin, 2021).

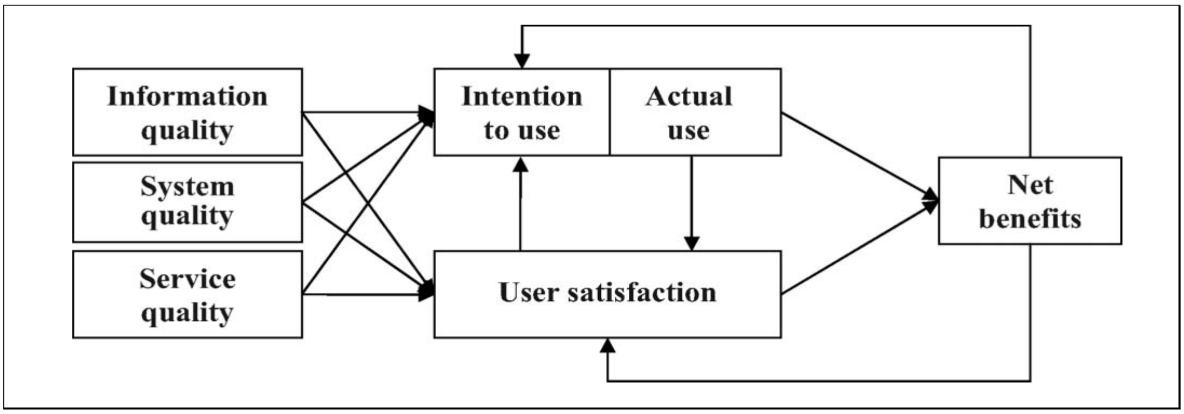
Figure 4 IS Success Model



(Source: DeLone and McLean, 1992)

Later, the D&M IS success model was criticised (Doll and Torkzadeh, 1998; Gelderman, 1998) due to the emergence of new technologies and new ways of organising and supporting IS technologies within organisations (Chen and Cheng, 2009; Aldholay et al., 2018). Thus, the need arose to rethink the determinants of use and satisfaction and adopt a broader conceptualisation of impacts. DeLone and McLean (2003) introduced the revised D&M IS success model that takes into account updates since 1993 (Figure 5). The update of the IS success model mainly includes the addition of service quality as a system attribute, the distinction between intention and actual use of the system and the collapsing of individual and organisational impacts into an overarching net benefits construct.

Figure 5 Updated IS Success Model



(Source: DeLone and McLean, 2003)

However, even this updated D&M IS success model has been considered limited as it does not take into account different types of use, such as the difference between routine use and innovative use (Chen, 2010; Hou, 2012). While some users may use an IS system routinely, e.g., accessing only basic functions, others may use a system more innovatively, e.g., using more advanced or customized features (Saavedra and Bach, 2017). Thus, it may be necessary to extend the D&M IS model even further to incorporate different types of use, specifically innovative use of the IS systems (Popovič et al., 2010). The inclusion of both routine and innovative use within an IS success model may better explain the types of usage behaviours more likely to improve user satisfaction and individual performance (Hajri et al., 2014).

Moreover, the D&M IS success model does not include data quality as a system attribute. Data quality may be especially important for innovative use and user satisfaction in the context of a BI system (Wixom and Watson, 2010). Data quality can be added to the D&M IS success model to explain variations in use and user satisfaction (Cohen et al., 2016; Gonzales and Wareham, 2019). While information quality reflects perceptions of the content and format of system outputs, data quality reflects the completeness and integrity of the data captured and stored in the system (Luo et al., 2012). It is therefore useful to include both data quality and information quality in the D&M IS success model to explain innovative use and individual user satisfaction.

A third limitation is that the D&M model does not consider the differing information needs of users when accounting for the effects of use on performance. These differences in information needs arise from variations in the task complexity of the user. The effects of system use on a user's performance may depend on the underlying complexity of the decision tasks facing the user (Chen and Cheng, 2009).

Thus, this study makes three theoretical extensions to the D&M IS success model. First, it expands the use construct to include both routine and innovative use. Second, it includes data quality as a system attribute alongside those of system, information, and service quality. Third, it considers the potential moderating influence of task complexity on the link between system use and performance outcomes. These extensions to theory and the D&M IS success model for the BI context are developed next.

3.3 Routine versus Innovative System Usage

System usage is regarded as an important construct in the information systems environment. This is because information systems cannot deliver value if they are not used. However, past studies have been inconsistent in the way system usage has been conceptualised and observed. In many of these past studies, system usage has been measured as the frequency of use or number of times using the system (weekly, daily, and monthly), extent of use (i.e., the number of systems, sessions, displays, functions, or messages), user self-reports of whether they are light or medium or heavy users, quality of use, such as how well the user can learn and use the system, and duration of use, such as connect time per week, amongst others (Burton-Jones and Straub, 2006). However, these conceptualisations of use have been regarded as too simplistic (Burton-Jones and Straub, 2006; Jaklič et al., 2018), and their adoption has resulted in insufficient knowledge regarding system utilisation and how systems come to impact on individual user outcomes.

Burton-Jones and Straub (2006) argued that researchers need to re-look at the conceptualisation of usage behaviour and to better assess its complexity and understand its impact on individual user outcomes (Burton-Jones and Straub, 2006). Burton-Jones and Straub (2006) and Li et al. (2013) thus explain that system use should be described in terms of the *user*, the *system*, and the *task*. The user is referred as an individual using the system, while the system is regarded as an object being used to perform a particular function (task) (Jaklič et al., 2018). In this study, the user is the management accountant, and the BI is the system being used. Users of BI systems include individual managers who require more complete, accurate and timely information to make operational and strategic decisions about customers, financials, internal business processes, and the learning and development aspects of the organisation (Petrini and Pozzebon, 2009). If the BI system is being utilised in the performance of the tasks of the management accountants, then it may have a positive impact on their job performance and decision making.

Burton-Jones and Straub (2006) went further to explain that system usage can be further classified as routine versus innovative use (Burton-Jones and Straub, 2006). In this study's context, routine use refers to the use of basic functions of the BI system to support basic tasks (Luo et al., 2012), while innovative use implies a more emergent and exploratory use of advanced functions of the BI system to support emerging tasks (Li et al., 2013). Thus, routine use can be understood as the standard use of a system to support normal or regular tasks, and innovative use implies a more novel use of system functions to support enhanced work performance (Li et al., 2013).

In the BI context, routine use occurs when users use BI systems to extract pre-built reports only, but without using the more analytical features of BI systems. Innovative use occurs when users are able to use more advanced BI system features such as self-service tools, interactive visualization, predictive analytics and drill down functionality to support more advanced work and improve their individual performance (Li, Hsieh and Rai, 2013). Without innovative use, organisations are unlikely to benefit fully from their organisational information base to achieve *inter alia* cost savings and improved business processes (Grabski et al., 2011). The use becomes innovative use when using the combination of advance features of the BI system to enhance decision making and individual performance. For example, the user may use advanced features to predict the future market share of the firms. This may allow the individual users to take more innovative decisions (Hajri et al., 2014).

In the management accounting context, routine and innovative use of BI systems can be summarised as follows (Gartner, 2012) (Table 3):

Table 3 Summary of Routine and Innovative use

Routine Use	Innovative Use
Executing existing BI standards reports (i.e., cost centre reports).	Use of self- help service tools embedded on the BI to analyse information without the assistant of the IT practitioner.
Executing existing BI built queries (i.e., sales volume).	Use of interactive visualization to transform information to a visual form, allowing the user to understand information better.
Performing basic analysis (i.e., ratio analysis)	Use of predictive analytics to leverage on current and historic data to predict the future (i.e., forecast)
Extracting raw data from BI tools and preparing reports in Excel (i.e., general ledger).	Use of drill down functionality allows the user to go deeper into the information to be analysed.

Routine Use	Innovative Use
Running ad-hoc reports (i.e., monthly financial report measuring cash flow)	Use of dashboards allows displaying key performance indicators in a visual format.
Cleansing data (i.e., eliminating redundant profit centres)	Use of the BI query functionality to develop customised reports that meet the need of the user.
	Use of trend analysis to understand current and future movement using time series data.
	Use of scenario planning to perform 'what-if' scenarios and make better decisions on the best possible future scenario.

Hou (2012) investigated factors that influence the individual usage of BI systems. The findings indicate that high levels of BI system usage can lead to improvement in individual performance. The findings were consistent with previous studies in other contexts (Chen, 2010; Cohen et al., 2016; Gelderman, 1998; Gaardboe, Sandalgaard and Nyvang, 2017). However, these studies have not distinguished between routine use and innovative use of systems and the need exists for additional research that examines the factors influencing the innovative use of BI systems over and above routine use by individual decision makers within organisational settings.

Although the implementation of BI systems has started to have an impact on individual users and organisational outcomes (Wierder and Ossimitz, 2015), Wixom and Watson (2010) have argued that the benefits of implementing BI systems are not always fully realised and argue that the realization of benefits depends on the manner and extent to which individuals use the available BI systems. For benefits to be realised from a system, an organisation should encourage individual system users to move beyond basic or routine use and towards more innovative use.

Hajri et al. (2014) stated that innovative use of information systems may minimise costs and time while improving productivity, quality of product and decision making. This may also improve the benefits that the organisation may derive from the system and thus justify the investment made. Users however are often more comfortable with the basic use of 'built–in' reports, while ignoring the more advanced features of an information system. In their study of innovative use of ERP systems, they found that organisational factors such as environment, organisation structure and user support can promote more innovative use. However, there remains a need to examine how system attributes (i.e., system quality, service quality and information quality, among others) can impact on the innovative use of systems and the consequent implications for job performance, productivity and decision-making quality.

While DeLone and McLean's (1992) Information System success model has been extensively used to explain factors influencing system usage at an individual level, it is not sufficiently tested whether the D&M IS success model factors explain innovative use as compared to routine use. It may thus be a relevant theoretical lens through which to examine the innovative use of BI systems by management accountants. In particular, the D&M IS success model identifies information quality, system quality, service quality, and user satisfaction as important factors that influence IS system use at the individual level (DeLone and McLean, 1992, 2003). In addition, there is a need to consider whether individual level factors such as the user's computer experience, level of training, and self-efficacy for innovative use interacts with the D&M IS success model factors to influence the degree of innovative use of a BI system (Schierder and Gluchowski, 2011).

3.4 Data Quality as a System Attribute

The second theoretical extension made by this study is the incorporation of data quality into the BI system success model. As indicated above, DeLone and McLean initially included into their model only system quality, i.e., usability, availability, reliability, adaptability, portability, integration and response time, and information quality i.e., content and format of the system's outputs to ensure they are *inter alia* useful, relevant, and understandable (Delone and McLean, 2003). However, these were necessary but not sufficient to explain IS user satisfaction and use, and which led them to subsequently include the component of service quality. Service quality is defined as the support that the user receives when using the IS, such as the ability for the support team to respond on time to user queries (Delone and McLean, 2003). Other studies (Işik, Jones and Sidorova, 2013; Cohen et al., 2016; Torres and Sidorova, 2019) however, have argued that data quality may be a further necessary system attribute distinguishable from system and information quality attributes. In a BI environment, data is abstracted from various internal and external sources through the Extract, Transform, Load (ETL) tool. The data abstracted includes both transactional and master data (Muhammad et al., 2014). In an organisation, the quality of data has an impact on providing useful information for decision making. The BI system obtains data from various systems and applications, consequently this can have an impact on data quality that might lead to decreased confidence of the user in BI reports (Torres and Sidorova, 2019). Furthermore, good quality data can lead to an improvement in user's confidence in BI information for decision making. This can result in a user relying more on the BI system to perform their functions. It is important that organisations should give special attention to the improvement of data quality so that incorrect decisions are not taken (Chen, 2010). The increase in demand for processing large volumes of data is driving the adoption of BI systems across organisations. The user's attitude towards the BI system as a solution to growing complexity and volumes of data is dependent on the quality of data and the trust that the user has in the BI system data (Torres and Sidorova, 2019). Côrte-Real, Ruivo and Oliveira (2020) stated that better data quality is needed as part of the BI system to create business value for users. Data qualities can be considered along dimensions of completeness, accuracy, consistency, conformity, redundancy, and integrity (Işik, Jones and Sidorova, 2011). The importance of data quality is clear as users can only make data driven decisions based on such qualities of their data. This can allow the user to rely on the data stored in the BI data warehouse. Gartner (2012) stated that data quality problems have been part of the top three problems that impact the successful use of BI systems. In the absence of sufficient data quality, data cannot be relied on. To improve the use of a BI system, it is appropriate to include data quality as one of the attributes alongside information quality, system quality and service quality (Côrte-Real et al., 2020). The inclusion of data quality will aid in improving user satisfaction and the use of the BI system and subsequently, job performance and productivity (Luo et al., 2012; Torres and Sidorova, 2019).

3.5 Task Complexity of the User

The third theoretical extension this study makes to the DeLone and McLean model is the inclusion of task complexity. Task is a set of assigned goals to be achieved, including instructions to be performed (Dehning, Richardson and Zmud, 2003). Tasks play a critical role in an information system (IS) environment. IS can structure or automate some tasks, some tasks that are unstructured can be supported with information from an IS, while other tasks can be transformed by IS, such as allowing them to occur in different locations or be carried out by different people than originally possible (Goodhue and Thompson, 1995; Li, Yuan and Che, 2021). The differences in the characteristics of tasks can mediate the relationship between IS use and performance. One of the important characteristics of a task is its complexity. Although the IS can be used to simplify the task, it is important to note that tasks are becoming more complex as technology is evolving (Liu and Li, 2012; Li and Liu, 2019). The introduction of new technologies, such as BI systems, has left the individual users of the system being exposed to more complex tasks (Nkwe, 2018). Complex tasks are usually not highly structured, they are often ambiguous as the outcomes are unpredictable and they are challenging to perform (Bonner, 1994). It is reasonable to assume that higher complexity tasks require special skills, knowledge, problem solving, IS support and additional task effort as compared to lower complexity tasks (Ain et al., 2019). The complexity of problem solving, and decision-making tasks would also affect how individuals use technology and to what extent technology would be useful in improving performance in tasks (Liu and Li, 2012). The relationship between IS use and individual performance would then be moderated by task complexity (Nkwe, 2018).

Examining how task complexity influences IS usage and subsequent net benefits has previously been raised in connection with the D&M model (Petter, DeLone and McLean, 2008; Chen and Lin, 2021). Their findings suggested a moderate positive relationship between task complexity and net benefits. This suggests that a high level of task complexity encourages the use of IS systems to improve net benefits (Li and Liu, 2019). Others have also examined task complexity in relation to performance. For example, Liu and Li (2012) examined task complexity as a mediator of routine use and performance, and Goodhue and Thompson (1995) studied task complexity as a function of use and performance. Those articles suggest that task complexity has a direct positive mediating effect on use and performance. Yet, Campbell (1988) in their study of task complexity review and analysis, found that task complexity had no influence on the effects of IS use on performance. That study however did not differentiate the type of use and gives an incomplete understanding of how use is affected by task complexity.

There remains a need to extend task complexity into the context of BI use and individual level performance of management accountants. This is because individual management accountants are using BI systems to support the task they perform (e.g., costing, budgeting, forecasting, reporting, and planning), and these tasks may range from structured and predictable to highly unstructured and ambiguous (Hadid and Al-Sayed, 2021). Hajri et al. (2014) suggested that users with more complex tasks are more likely to use innovative features of BI systems to improve their performance. However, the way task complexity interacts with BI use has not received sufficient attention. The impact of task complexity in both routine and innovative use is not fully understood (Li et al., 2013). Previous studies investigated innovative use without including task complexity as a moderating effects or control variable (Hajri et al., 2014; Li et al., 2013). Given that research into task complexity and IS usage is still emerging (Liu and Li, 2012), it is important to continue to investigate the ways in which task complexity affects IS use (innovative and routine use) and its relationship with individual user performance.

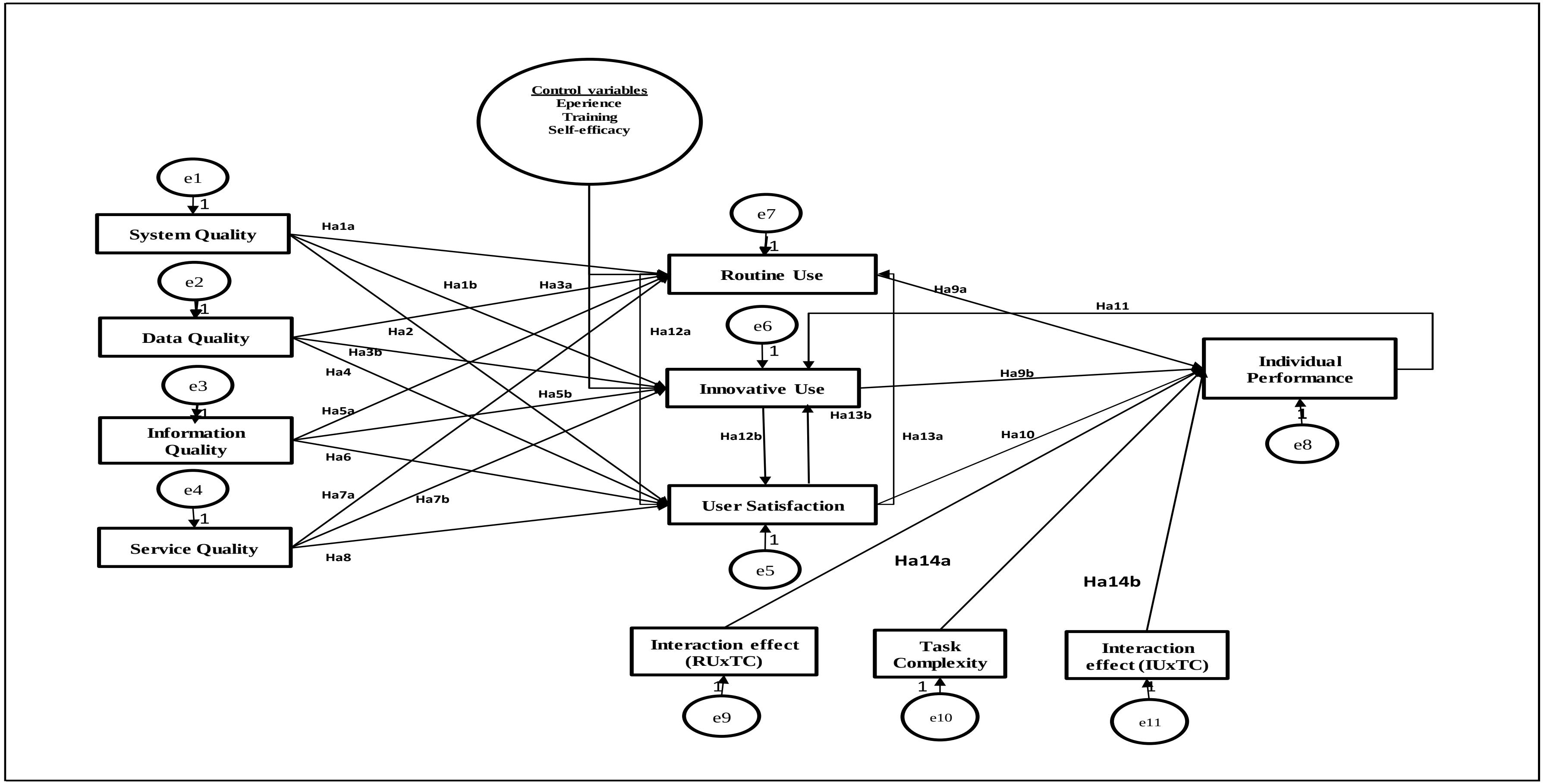
Moreover, users can use the BI system in a routine way while they find new ways of performing tasks (Luo et al., 2012). In a normal day, use of the system can vary between innovative use and routine use, based on the complexity of the task. There is a need to investigate whether users facing less complex tasks may only need routine features and functions, while users facing more complex tasks may rely on more innovative features in their BI usage (Li et al., 2013). Use of the innovative features may be required to find solutions to more complex decision problems. As task complexity increases, users may shift from routine toward innovative use (Luo et al., 2012).

Drawing on this D&M IS Success theoretical underpinning and the proposed extensions, a research model, and hypotheses for the study of individual BI users can be formally developed next.

3.6 Development of Research Model and Hypotheses

The extended D&M success model for the BI context research model is depicted in Figure 6. The research model incorporates four system attribute variables, namely information quality, system quality, service quality and data quality as determinants of user satisfaction, routine use, and innovative use. They are in turn, hypothesised to impact individual performance. The complexity of tasks facing the user may intervene as moderating effects. Through the literature, thirteen hypotheses are developed and are tested over three time-waves ($w_{1,}$ w_2 and w_3) to address research questions (RQ1 and RQ2).

Figure 6 BI Success Model



Source: Researcher's Own work

3.6.1 The Research Model has Three Dependent Variables. Use, User Satisfaction and Individual Performance

Individual performance is defined as the job-related activities assigned to an employee and the extent in which those activities are executed by that individual (Wang et al., 2007). Decision-making speed and quality, and individual productivity and effectiveness are example indicators of individual job performance (Hou, 2012; Isaac et al., 2017).

User satisfaction is a specific attitude that the user displays towards the use of the information system application (Bokhari, 2005; Saavedra and Bach, 2017). According to Wu and Wang (2006) it is difficult to “deny the success of a system which users say they like”; thus, “user satisfaction is also a good measurement for BI systems success” (Wu and Wang, 2006; Serumaga-Zake, 2017). User satisfaction refers to the way the user feels about the IS (Delone and McLean, 2003).

As previously discussed, use is considered in terms of routine use and innovative use. Routine use is referred to as the use of basic functions of the BI system to support basic tasks (Luo et al., 2012). Innovative use implies a more emergent and exploratory use of advanced functions of the BI system to support emerging tasks (Li et al., 2013).

The hypotheses linking system attributes to use and user satisfaction are developed next.

3.6.1.1 System quality

System quality refers to the characteristics that include system usability, availability, reliability, adaptability, portability, integration, and response time (Petter et al., 2008; Serumaga-Zake, 2017). System quality plays a significant role in influencing system use and user satisfaction (Popovič et al., 2012; Wixom and Watson, 2010; Delone and McLean, 1992, 2003; Petter et al., 2008; Gaardboe et al., 2017). In the BI context, a high-quality system can influence the user to use the BI systems innovatively, e.g., a more usable IS system provides an opportunity to the user to use more complex functionality (such as a self-service tool) to search for the information or report needed (Wixom and Watson, 2010). A user is more likely to enjoy using a system that is easier to use, will be happier and less frustrated (Montero, 2019). Therefore, it is hypothesised that:

Ha1(a and b): Perception of system quality will have a positive impact on routine and innovative use of BI systems by management accountants; however, it will have a stronger impact on innovative use than on routine use.

Ha2: Management accountant perceptions of BI system quality has a positive impact on user satisfaction.

3.6.1.2 Data quality

Data quality refers to the unprocessed data records that are stored within the computer system (Popovič et al., 2012). The introduction of IT systems has helped to ensure that data records are available, complete, and accurate. Data records can be used as input for further processing by individual management accountants in executing their tasks (i.e., planning and controlling). If the input data records are of poor quality, users will not trust the system and are less likely to use the system (Côrte-Real et al., 2020). It is important that data is complete, accurate and consistent amongst all the data sources (Petter et al., 2008; Torres and Sidorova, 2019). The users are more likely to use the system innovatively if data stored is trusted to be of a good standard and this may improve user satisfaction (Chen, 2010). In the context of BI systems, data quality refers to management of data stored in the data warehouse, extracted from various internal and external sources using ETL tooling. Data is transformed to the format required by the structure of the data warehouse before it can be stored. Once the data has been stored on the data warehouse, it is made available for use (Montero, 2019). Therefore, the quality of the data stored is important in ensuring that users can rely on the system. Good quality data exist only when data is suitable for use. Therefore, it is hypothesised that

Ha3 (a and b): Perception of data quality will have a positive impact on routine and innovative use of BI systems by management accountants; however, it will have a stronger impact on innovative use than on routine use.

Ha4: Management accountant perceptions of data quality has a positive impact on user satisfaction.

3.6.1.3 Information quality

Information results from data that has been processed to become meaningful for decision making. Information quality refers to the content and format of the system's information outputs. Information outputs should be accurate, useful, relevant, complete, and understandable if they are to be helpful for planning and decision making (Delone and McLean, 1992; Gonzales and Wareham, 2019). If the information output produced by the IS system is of poor quality, then a user may not want to use the system (Delone and McLean, 2003; Petter et al., 2008). In the context of BI systems, accurate and relevant information output is especially likely to influence use and improve user satisfaction (Popovič et al., 2010; Ojo, 2017). When better quality information is produced by the BI system, a user may also be motivated to use the BI system more innovatively to support their work (Popovič et al., 2012). Therefore, it is hypothesised that:

Ha5 (a and b): Perception of information quality will have a positive impact on routine and innovative use of BI systems by management accountants; however, it will have a stronger impact on innovative use than on routine use.

Ha6: Management accountant perceptions of information quality will have a positive impact on user satisfaction.

3.6.1.4 Service quality

Service quality refers to the support that the user receives when using the IS (Serumaga-Zake, 2017). IS support is normally provided by the service provider or internal IS department. Service quality can be measured inter-alia through perceptions of service attributes such as tangibility, reliability, responsiveness, assurance, and empathy (Delone and McLean, 2003). The availability of IS support services may assist users to gain confidence in using their BI system, and proper support may even result in their using the BI system more innovatively. This may be especially so if IS support teams are dedicated to assist users in operating the system's functions such as self-service tools, interactive visualization, predictive analytics reports and drill down (Popovič et al., 2014; Ojo, 2017). Without such support, a user is less likely to move beyond basic routine levels of use. Service quality may also have an impact on user satisfaction. Employees who feel more supported by a responsive, reliable and capable team to use the functions of their BI system and who believe IS services help to ensure the system's availability at the times required are likely to be overall more satisfied with the BI in support of their work (Ameen et al., 2020). This service level is likely to help users feel more satisfied with the decision to use the system. Therefore, it is hypothesised that:

Ha7 (a and b): Perception of service quality will have a positive impact on routine and innovative use of BI systems by management accountants; however, it will have a stronger impact on innovative use than on routine use.

Ha8: Management accountant perceptions of service quality will have a positive impact on user satisfaction.

3.6.1.5 Use and Individual performance

The individual performance impact of an IS can be measured by its contribution to "decision-making quality", "job performance", "individual productivity", "job effectiveness", "problem identification speed", "decision-making speed", and "the extent of analysis in decision-making" (Hou, 2012; Isaac et al., 2017).

Routine use can help management accountants by abstracting standard reports (cost centre report, profit centre report, variance analysis, ratio analysis, balance sheet and cash flow) that can be used to prepare normal management accounts used for tracking performance to date against the target set (Luo et al., 2012). Routine use can only help management accountants to perform their normal basic functions that are not complex in nature. These features are not enough to perform complex management accounting functions, such as forecasting, costing, scenario planning, key performance indicator monitoring, visual display of key information, dashboard display, trend analysis and interactive customised reports to meet the needs of management (Hadid and Al-Sayed, 2021). Hence, there is a requirement for innovative use of systems to handle more complex management accounting functions (Vakalfotis et al., 2011).

The concept of innovative use extends routine use and, in the context of BI, refers to the use of more advanced BI system features such as self-service tools, interactive visualization, predictive analytics reports and drill down functionality (Hajri et al., 2014). Such innovative use of BI systems to support work may improve individual performance, e.g., by aiding users in analysing the possible future outcomes of a decision taken (Chen and Cheng, 2009). By helping management accountants to perform complex management accounting tasks, innovative use of BI systems is expected to impact their individual performance along indicators that include decision making quality, job performance, productivity, decision speed and effectiveness (Hou, 2012; Montero, 2019). Improving performance may require more use of innovative features of the BI system as compared to routine use. By examining both the determinants and consequences of BI systems use, BI systems can be better designed and managed to meet the end-user's expectations, facilitate more complex decision-making tasks, and improve their decision-making performance (Li et al., 2013). Therefore, it is hypothesised that:

Ha9 (a and b): Both routine and innovative use of BI system will have a positive impact on individual performance, however innovative use has a stronger impact on individual performance than routine use.

3.6.1.6 Use satisfaction, Use and Individual performance

Previous researchers have identified user satisfaction as one of the key IS success measures frequently used and should be an important element of BI system evaluation (Delone and McLean, 2003; Chen, 2010; Petter et al., 2008; Isaac et al., 2017). If the system that the users are using is improving performance or decision-making, then users tend to use the system, otherwise they may avoid using the system unless it is a job requirement. Even in workplace contexts, the manner in which continued use of a system occurs, may depend on the satisfaction and judgement of its users.

User satisfaction may also improve the user's job performance and decision making (Chen, 2010; Serumaga-Zake, 2017). Prior studies have supported the positive impact of user satisfaction on individual performance (Wang et al., 2007; Wu and Wang, 2006; Chen, 2010; Angelina et al., 2019). For example, Hou (2012) found that users who are satisfied with an IS system are more likely to report improved job accuracy, job performance and skills needed to perform their duties. Therefore, it is hypothesised that:

Ha10: Perceptions of user satisfaction will have a positive impact on individual performance of management accountants.

In the context of BI systems, the improvement in individual performance is expected to encourage the user to use BI systems even more innovatively. Thus, the relationship between use and performance may be reciprocal (Isaac et al., 2017). When the user experiences the BI system as improving the quality of their decision making, individual productivity and the speed taken to diagnose a problem, then a user is expected to engage more with the system to find new ways of using it in supporting their work (Hajri et al., 2014). Therefore, it is hypothesised that:

Ha11: Perceptions of Individual performance will have a positive impact on innovative use by management accountants.

In addition, the DeLone and McLean model suggests reciprocal links between use and user satisfaction. Li et al. (2013) argue that innovative use can result to user satisfaction as the users will be exploring more advanced functionality of the system in executing their tasks. System use is critical in user satisfaction as it measures the extent, nature, quality and the appropriateness of using the system. The nature of use then determines if the system is being used for its intended purpose. The extent of use then explains functionalities that are being used, some users only use the routine features while others use innovative features. The type of the use is important for the individual user's satisfaction (Hajri et al., 2014). The decrease in usage can be an indication that the system is not performing the way it was intended and user satisfaction may be affected (DeLone and McLean, 2003). The innovativeness of BI systems may improve user satisfaction beyond more routine levels of use. The users who use the system innovatively are expected to benefit more than users who engage only with default functionality (Angelina et al., 2019). These additional benefits will translate into a more positive evaluation of the system and reflect in the user's satisfaction. Hence:

Ha12 (a and b): Perceptions of routine and innovative use will have an impact on user satisfaction, however innovative use has a stronger impact on user satisfaction than routine use.

In turn, user satisfaction improves the intention to use the information system, if users are satisfied by the usage of the information system, they are likely to continue using the system. A system characterised by low levels of user satisfaction is an indication of frustrations and tension that may lead to decrease in usage. User satisfaction encourages the user to use the information system. User satisfaction is thus theorised to lead to more use of an IS over time (Wang et al., 2007). This may be especially so with more innovative uses. Therefore, it is hypothesised that:

Ha13 (a and b): User satisfaction will have a positive impact on routine and innovative use, however, impacts on innovative use will be stronger than on routine use.

The next sections discuss the role of task complexity and control variables.

3.6.1.7 Task complexity

The research model incorporates task complexity[1] as a moderating variable influencing the effects of use and satisfaction on performance. Task complexity is a critical task characteristic that influences a user's information seeking and search behaviour (Li et al., 2013). If a user with high task complexity is able, via the use of a BI system, to locate more useful information to support them in decision making, then their individual performance is likely to increase (Li and Liu, 2019). Thus, individual performance is improved when analysed information assists a user in taking complex decisions (Lin et al., 2009). However, a user facing low task and decision complexity may not necessarily require the same level of information support to perform in their job. Thus, it is expected that the link between use and performance will be stronger among individuals who have higher task complexity than among users with lower levels of task (Li et al., 2021). Users with more complex tasks will have more motivation to embrace innovative use and more advanced system features than users who see themselves as generally having fewer complex tasks (Li et al., 2013)

Ha14 (a and b): Task complexity will have a moderating effect on both routine and innovative use and performance; however, interaction with innovative use will have a stronger impact on individual performance than interaction with routine use.

3.6.1.8 Other controls

Self-efficacy is included as a control variable. It is defined as the belief that the individual possesses in their ability to execute the behaviour that assists in enhancing individual performance (Lin et al., 2009), i.e., in the ability to use the BI system. Users with low levels of self-efficacy will be less likely to use a system, and especially are less likely to extend into innovate use of more advanced system features.

Experience and training are also added as additional control variables. Experience refers to knowledge that is acquired while working in a particular field or organisation. Training refers to teaching or developing oneself or other skills or knowledge relating to a particular competency (Georgopoulos and Tannenbaum, 1957). Users with more experience are likely to experiment with more novel features. Training may help even less experienced users to find ways to use the system in performing their work and may introduce them to more advanced

[1] Although task complexity is hypothesised as a moderating variable, its direct effect is nonetheless still considered in the empirical test of this hypothesis.

features (Wu and Wang, 2006; Aldholay et al., 2018). More experienced users are also likely to use their BI systems without requiring much additional support.

3.7 Longitudinal Effects of Individual Use of BI systems

This section addresses research objectives RO2 which is to empirically evaluate the impact of innovative use of BI system on individual-level performance of management accountants. However, the approach taken is to test this over time using longitudinal methods. Delone and McLean (2003) suggest that to best understand the behaviour of users, it is necessary to test the IS success framework longitudinally, as there is always a gap between the implementation of the system and the actual use and between use and the outcomes of use. Longitudinal data can thus best test the implied causal linkages within the D&M model and to explain the determinants and consequences of user behaviour over time.

3.7.1 Individual Use and Causal Relationships

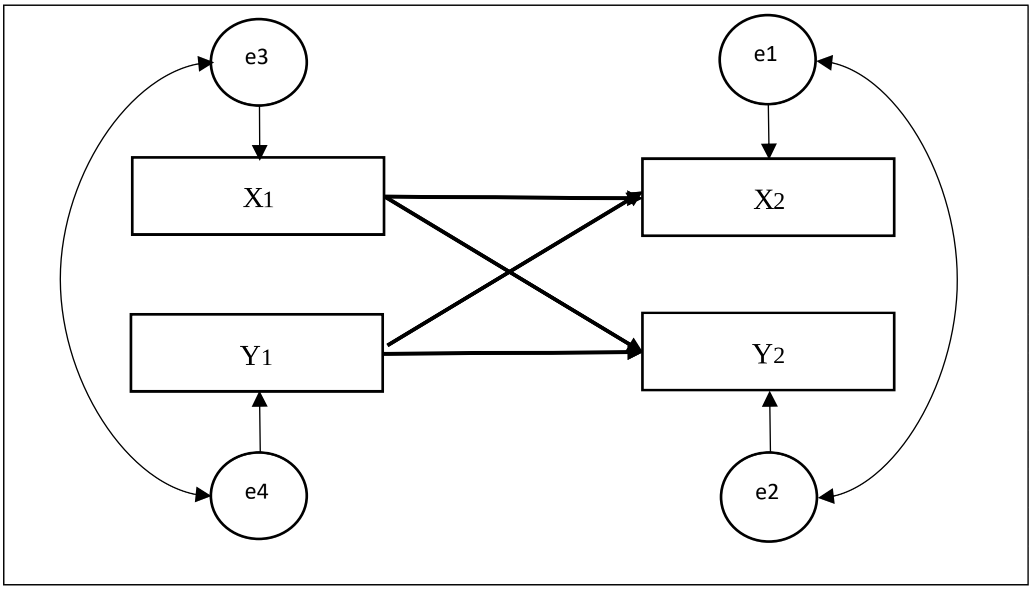
Causality can be defined as an element in which one occurrence in a particular condition has an influence on outcomes of another event and is the basis of good theory (Gregor, 2006; Son and Taamouti, 2019). The causality phenomenon has been a topic of intense deliberations in various disciplines. Understanding causality is not only important in predicting the relationships between constructs, but it can be used by researchers to provide practical guidelines, such as on how an information system can be used in practice (Gregor, 2006). The problem of how to establish causal connections has received much attention in other fields (e.g., psychology and marketing) (Lee et al., 1997; Zheng and Pavlou, 2010), while it has not received much attention in the IS field except for a few studies (e.g., Avgerou, 2013; Mingers, 2004; Mingers, Mutch and Willcocks, 2013; Smith, 2006; Markus and Robey, 1988; Gregor, 2006; Gregor and Hovorka, 2011; Hovorka, Germonprez and Larsen, 2008; Son and Taamouti, 2019).

Researchers have often relied on the use of cross-sectional data to make causal inferences. However, cross-sectional data does not establish temporal precedence between cause and effect. This severely limits the ability of researchers to make causal claims. There have been several methods used to measure causal relationships using cross-sectional testing. Lee et al. (1997) developed a TETRAD tool as a non-parametric software that assists in establishing causal relationship at an exploratory phase and to establish causal effect of the latent variables. Later, Zheng and Pavlou (2010) also developed the “Bayesian Networks for Latent Variables method which examines causal relationships". However, data collected from cross-sectional studies must always be interpreted with caution when inferring causality (Baumgartner and Homburg, 1996). Cross-sectional data has limitations when it comes to measuring causal models, as a result, researchers are advised to use longitudinal data to better establish causal relationships. Moreover, while cross-sectional data can be informative, results might also be misleading due to a common method bias element (Awang, Afthanorhan and Asri, 2015; Son and Taamouti, 2019).

Zheng and Pavlou (2010) and Hovorka et al. (2008) argue that longitudinal data allow for the better establishment of temporal precedence to evaluate causal relationships. Moreover, collecting data over time also reduces the susceptibility of studies to common method bias.

The development of Structural Equation Model (SEM) techniques provides an opportunity for cross-lagged models to be used to examine longitudinal data (Baumgartner and Homburg, 1996). In the cross-lagged analysis, two, or more, waves of data are used to evaluate causal relationships. For example, the technique allows for variable X at wave 1 to be tested with variable Y at wave 2 to establish if a causal relationship exists. The variables are thus measured on two or more occasions, supported by the covariance structural equation model analysis (i.e., AMOS or LISREL) to determine if there are changes in causes and effects of the two variables being measured. The example of causal relationships between variable X and Y at a different wave is illustrated in Figure 7. If variable X and Y are significantly correlated, this means that early-stage (X_1) may influence later-stage (Y_2). While longitudinal studies often ignore reciprocal causality within variables, cross-lagged models also allow for reciprocal causality to be considered (Mou and Cohen, 2008).

Figure 7 Example Cross-lagged Wave Model



(Source: Mou and Cohen, 2008)

The cross-lagged model allows researchers to understand patterns of covariation within variables by observing measured constructs over time. The approach allows for the establishment of cross-construct relations and for the causality to be tested in both directions (e.g., whether the independent variable influences the dependent variable or vice versa).

3.7.2 Causal Relationships in Information System

Prior papers (Mou and Cohen, 2008; Mingers, 2004;) that have spoken of the need to understand causal relationships on some of the relationships not fully understood in causality, include intention to use↔individual outcome (Mingers, 2004), user satisfaction↔individual outcome (Benlian, 2015), data quality↔ user satisfaction (Petter et al., 2013), routine use ↔performance (Benlian, 2015), and innovative use ↔ performance (Kim, 2009). This study focused on the causal relationships amongst routine use, innovative use, user satisfaction and individual performance. The causal relationships amongst these variables have not been fully understood (Benlian, 2015; Zheng and Pavlou, 2010; Kim, 2009; Grover, 2019; Mingers et al., 2013). Most of the studies that examine use, user satisfaction and performance rely on cross-sectional rather than longitudinal data (Wang et al., 2007; Wu and Wang, 2006; Chen, 2010; Drake and Martin, 2020; Ashrafi et al., 2019; Liew, 2019). Therefore, the causal relationships between use, user satisfaction and performance must still be established. The use of cross-lagged model structural equation modelling, along with longitudinal (time-wave) data, to examine causal relationships in IS research has been very limited. No study so far has investigated the causal relationships between routine use, innovative use, user satisfaction and the individual performance phenomenon (Benlian, 2015). It is imperative that causal relationships using techniques, such as cross-lagged models, be established to understand if early use of the system affects late-stage individual level performance of management accountants, and whether user satisfaction changes over time and affects later-stage individual use and/or performance, along with any reciprocal effects over time waves. The need to understand the dynamic nature of innovative use, user satisfaction and individual performance is thus of theoretical and practical interest (Kjeldskov et al., 2010; Markus and Rowe, 2018; Carstensen, 2012; Venkatesh and Davis, 2000). This better understanding will assist with the justification for investments in the implementation of the BI system and better management of system use over time, including ways to encourage use of more advanced features of the information system. Organisations are implementing BI systems, however there is a variation of usage among management accountants. It is important to understand whether routine or innovative use over time may improve individual performance of management accountants and how use and user satisfaction interact over time to improve individual performance. This may provide an explanation on why some management accountants are continuing to use Excel after the implementation of BI systems (Rom and Rohde, 2006; Abdusalomova, 2019). The use of cross-lagged structural equation models to explore this issue constitutes a methodological contribution and addresses limitations in previous IS research work. Measuring usage in three different waves from early-usage activities to late-usage activities also improves understanding of factors relevant to the continued use of information systems (Jasperson, Carter and Zmud, 2005; Grover, 2019). Although, information system use is a key construct of IS research, most studies applied cross-sectional designs in measuring its effects on performance (Cohen et al., 2016; Courtois et al., 2014; Chen, 2010; Chen and Cheng, 2009; Ameen et al., 2020). There are some exceptions. For example, Benlian (2015) investigated use of IS features over time and the impact on task performance. They found that extensive use of the features of IS over time improves performance through feedback mechanisms. The improvement is through positive feedback that encourages users to use more features of the information system over time (Kim, 2009; Kim and Malhotra, 2005; Markus and Rowe, 2018; Carstensen, 2012). However, that study did not differentiate whether it is the continued use of basic features or the advanced features of the IS that influences performance over time. Mendoza, Carroll and Stern (2008) argued that IS use changed with time as users adapt to a new technology in different ways. As users gain experience and confidence with the new system, they explore the new features provided by IS or try new features of the IS. Thus, innovative use may only occur at later stages as increase in using novel features evolves over time. Mendoza et al. (2008) found some users to use limited features of the IS because they did not see the benefits of using it, even though they had expected to derive benefits initially during the early-stages of use. Tracing user over time allows for a determination of the extent to which the fulfilment of early expectations (i.e., satisfaction) is important to subsequent use (Smith, 2006; Markus and Robey, 1988; Markus and Rowe, 2018).

3.7.3 Cross-lagged Individual Models

The challenges raised above require that the relationships of use, user satisfaction and individual performance be examined over time[2]. This is achieved in this study by using three cross-lagged models. Model one (M1) is the relationship between W1 (innovative use, routine use, and user satisfaction) and W2 (individual performance and innovative use). Model two (M2) is the causal relationship between W2 (innovative use, routine use, and user satisfaction) and W3 (individual performance and innovative use). Finally, Model three (M3) investigates the causal relationship between W1 (innovative use, routine use, and user satisfaction) and W3 (individual performance and innovative use). Therefore, this section aims at demonstrating the relationship between the innovative use of BI systems by individual management accountants and user satisfaction and individual performance over time. Furthermore, examining these cross-lagged models provides an opportunity to better understand any reciprocal relationships between use, user satisfaction and individual performance in the context of BI systems. The three models tested using cross-lagged structural equations are presented below namely, M1 (W1 to W2) (Figure 8), M2 (W2 to W3) (Figure 9), and M3 (W1 to W3) (Figure 10).

[2] Some longitudinal studies might examine effects over time using the (delta or) difference between observations at each wave. The cross-lags approach focuses on the lagged effect of early-stage variables on later stage outcomes along with reciprocal effects as suggested by the theoretical model.

Figure 8 Model 1(W_1 to W_2)

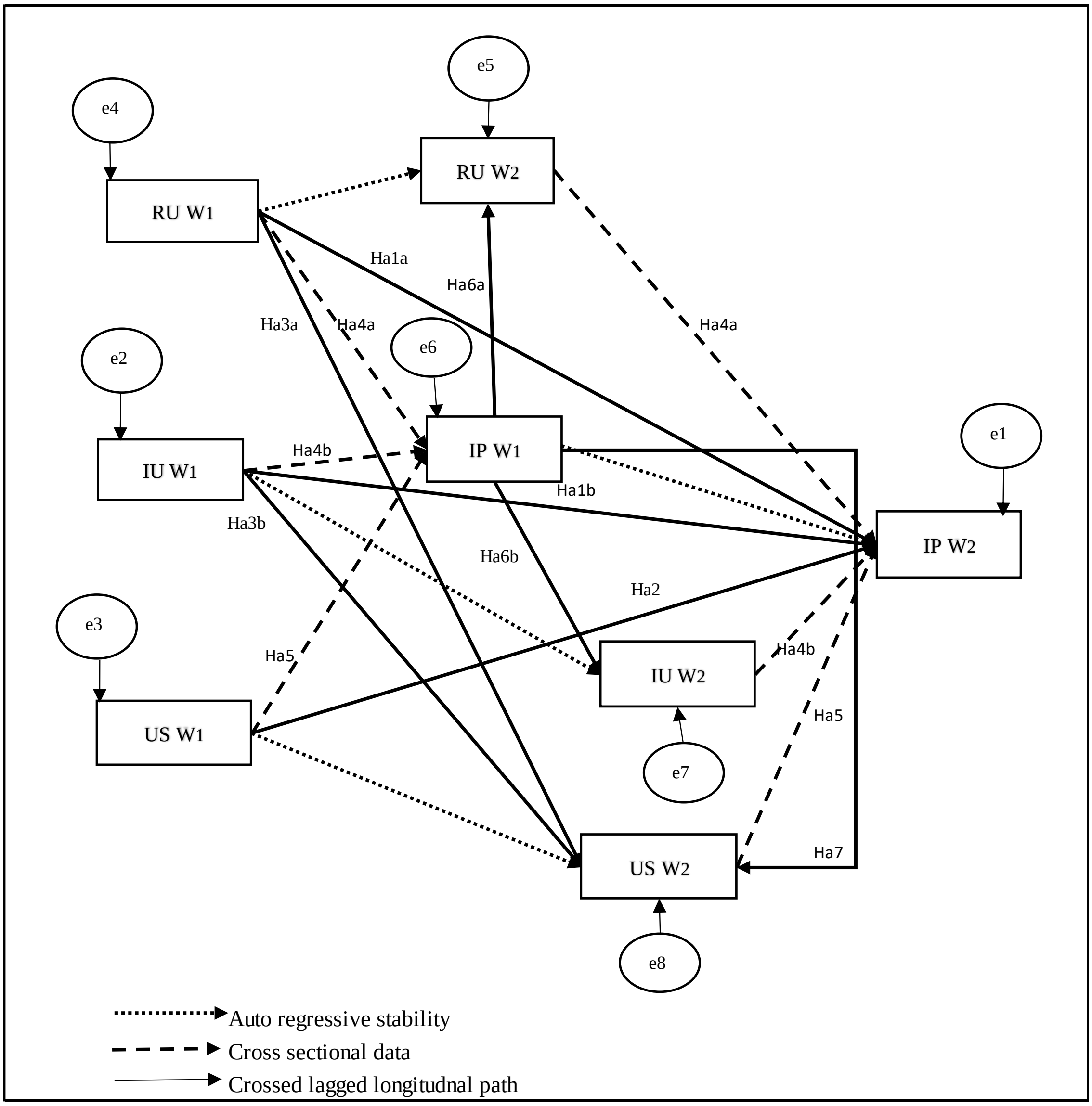


Figure 9 Model 2(W_2 to W_3)

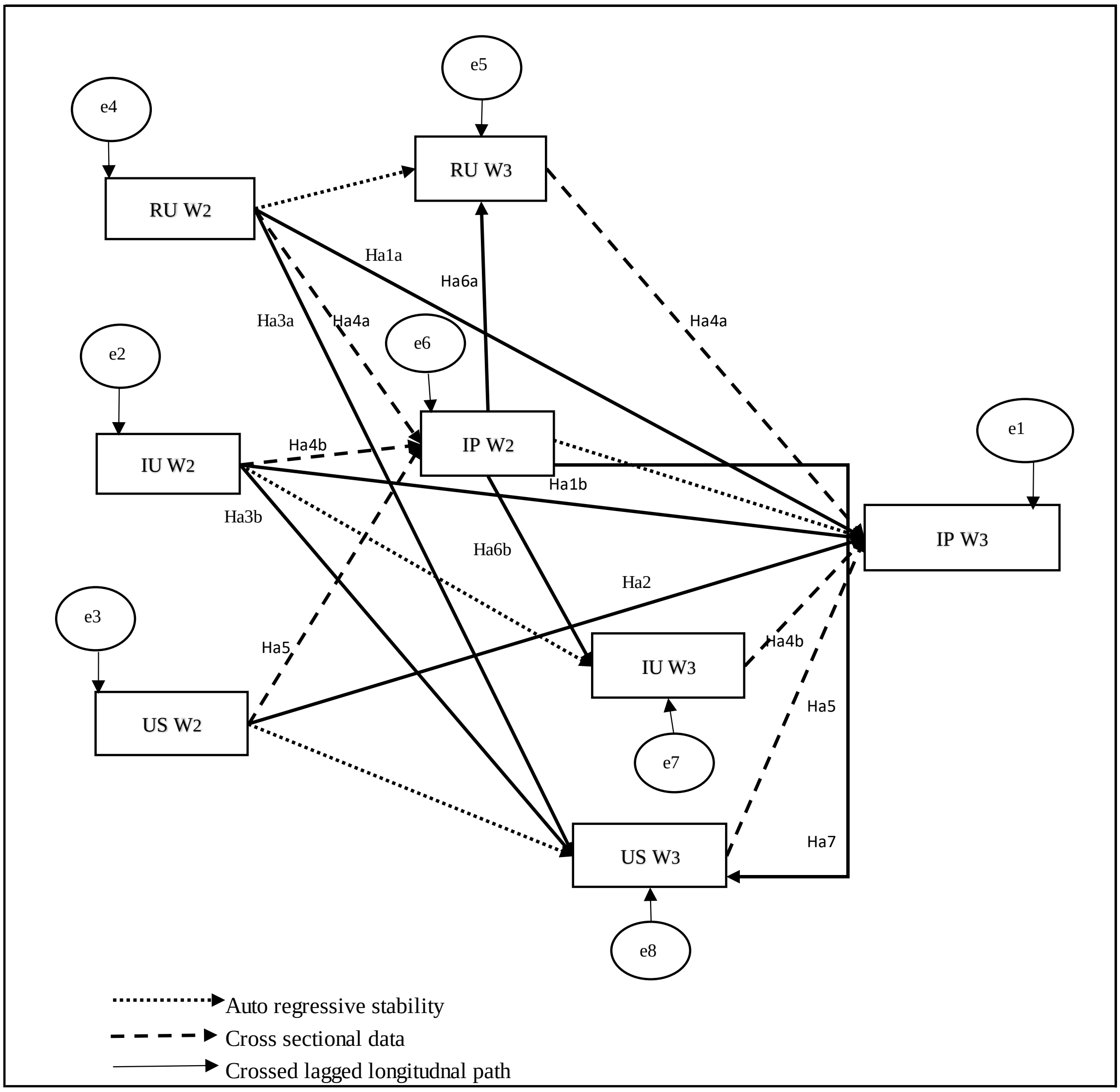
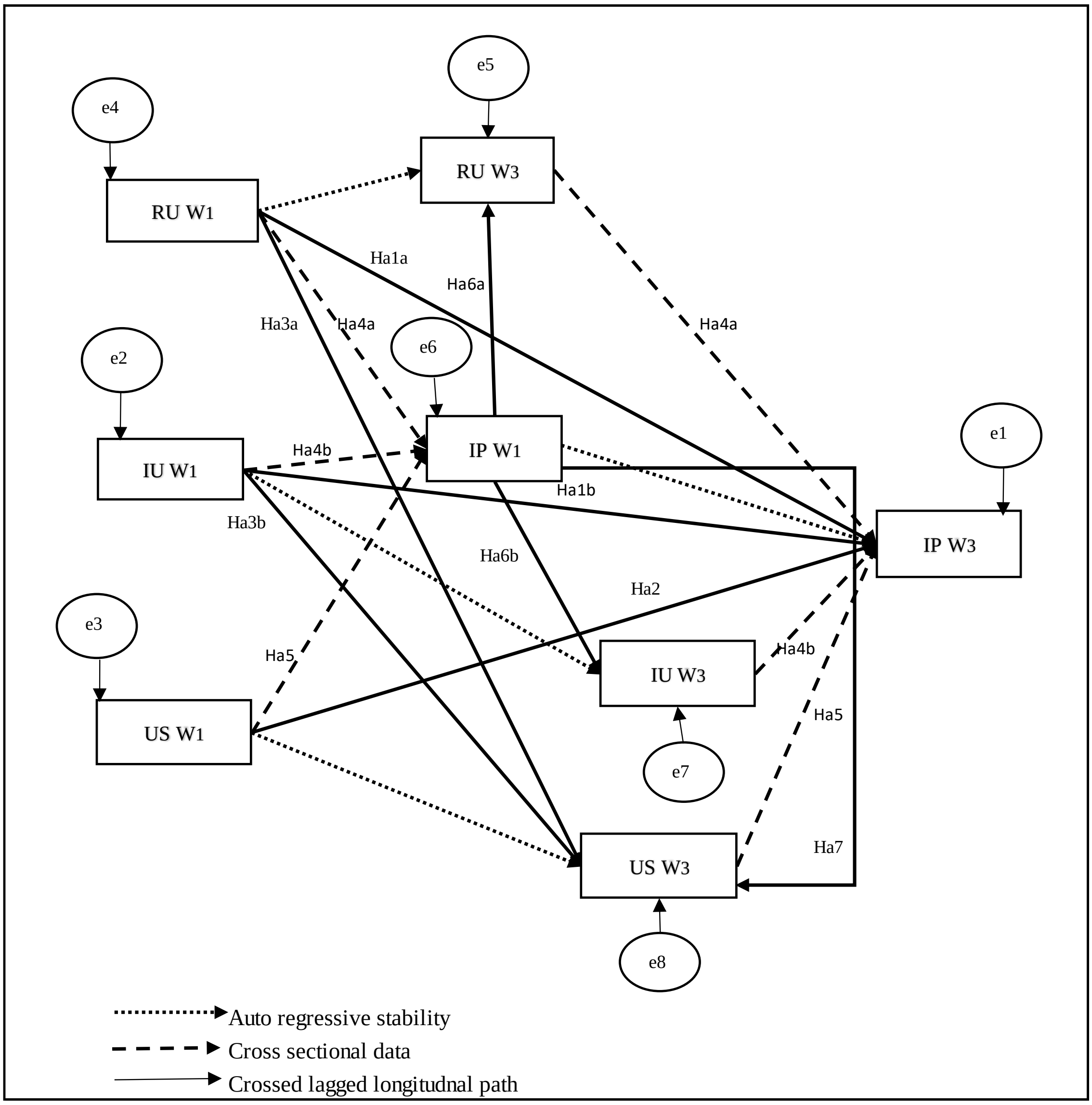


Figure 10 Model 3 (W_1 to W_3)



The relationship between early use and later performance may be reciprocal. The early use of the BI system may improve later individual experiences on quality of decision making, individual productivity and the speed taken to diagnose a problem (Benlian, 2015).

Importantly, a user is expected to engage more with the system to find new ways of using it in supporting their work (Hajri et al., 2014). Furthermore, early-stage performance improvement may contribute to later-stage use and result in users using more innovative features of the BI system, such as predictive analytics, in supporting their work. The D&M model suggests the reciprocal links between early use and later user satisfaction. Li et al. (2013) stated that early-stage innovative use can result in later-stage user satisfaction as the users will be exploring more advanced functionality of the system in executing their tasks.

3.8 Conclusion

This chapter has developed an extended D&M IS success model of the factors influencing innovative use of BI systems and the subsequent impacts on individual performance. The model represents several extensions over the original D&M model. It has included data quality, distinguished between routine use and innovative use, and considered the effect of task complexity. Moreover, the chapter addresses the limitations of past studies to address causal ordering between use, user satisfaction and individual user performance by hypothesizing a set of cross-lagged models.

There is a need to understand whether the innovative use of BI systems can improve the individual job performance of management accountants over time. This is part of the bigger problem of trying to justify the investment made in BI systems from a South African context.

The next chapter discusses the organisational impact of BI systems and develops the organisational level research model with the hypotheses to be tested.

CHAPTER 4: RESEARCH MODEL ON THE ORGANISATIONAL IMPACTS OF BI SYSTEMS

4.1 Introduction

In chapter 3, a research model of the individual use and impacts of BI systems was developed and associated hypotheses presented. This chapter develops the research model proposed to address the study's third research objective (RO3) and research question (RQ3). Specifically, "*to identify the impact of BI systems on the sophistication of management control systems (MCS) as well as on a balanced set of organisational performance outcomes (financial and non-financial performance)*". RQ3 is answered by drawing *inter alia on the "Balanced Scorecard (BSC) performance measurement system and conceptualising the sophistication of MCS in terms of formal and informal controls"* (Kaplan and Norton, 1992; Kallunki et al., 2011). First, in the next section of the chapter, the balanced scorecard (BSC) model is introduced and explained in detail as the basis for examining the financial and non-financial performance impacts of BI systems within organisations. Next, formal, and informal management MCS are explained as intermediary mechanisms linking BI to performance. The research model and hypothesis are then developed.

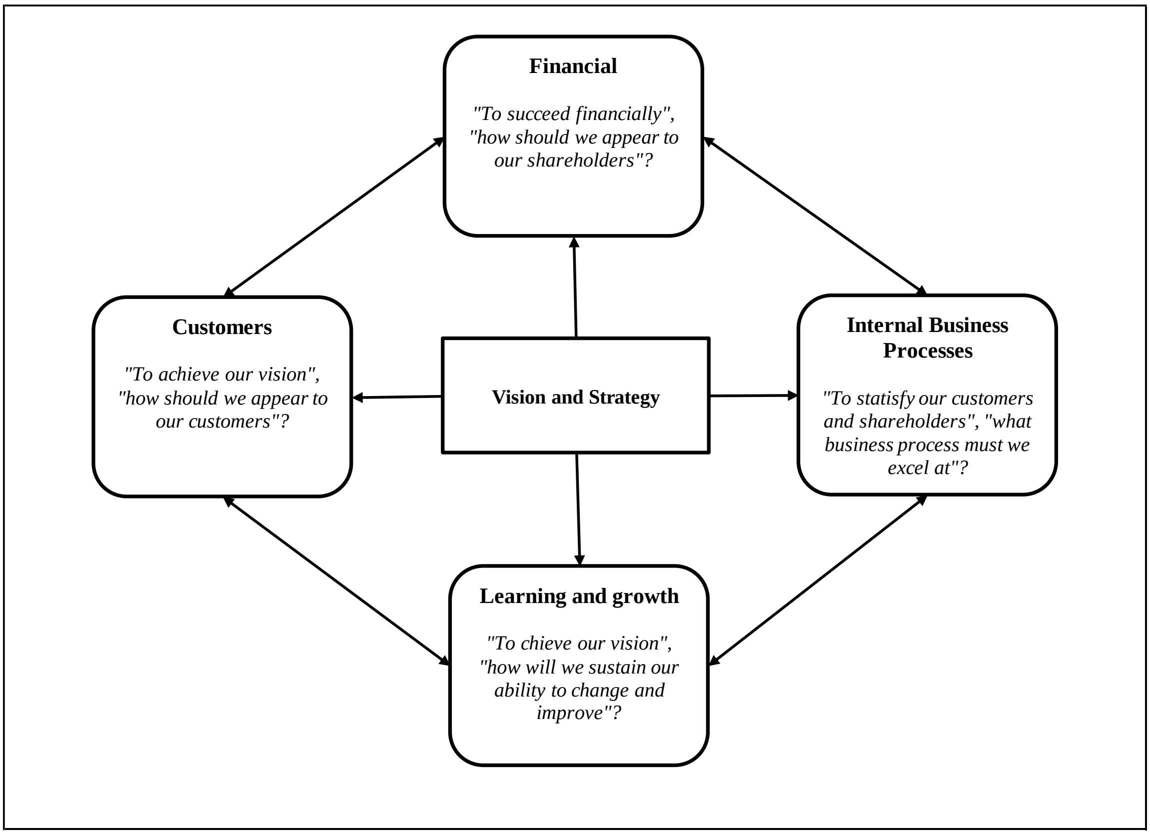
4.2 Organisational Performance and the Balanced Scorecard

Organisational performance has been defined in various ways in management research due to its different meanings. Georgopoulos and Tannenbaum (1957) defined organisations as a social system aimed at fulfilling a set of objectives and thus evaluate performance in terms of work, people, and structures. Seashore and Yuchtman (1967) defined organisational performance as the ability of an organisation to exploit its environment and access and use limited resources. In addition, organisational performance was further defined as the accomplishment of organisational goals using limited resources (Gavrea, Ilies and Stegerean, 2011). These latter definitions promoted a financial performance focus (i.e., on profitability, return on assets, etc.). However, financial performance alone cannot provide a holistic measure of organisational performance (Gavrea et al., 2011; Drake and Martin, 2020).

Therefore, Kaplan (2006) further explains the concept of organisational performance as a balanced set of outcomes that includes both financial and non-financial performance and captured these in his balanced scorecard (BSC) framework, Figure 11. The main definition of organisational performance includes performance measures as a set of financial and non-financial performance indicators, which provide information on the achievements of the organisation against its objectives and the set results (Kaplan, 1992).

Kaplan and Norton (1992) introduced their BSC approach based on a realisation that financial performance is not the only relevant measure of organisational performance. Specifically, the BSC introduces four integrated perspectives on performance. These perspectives can be categorised into financial performance (financial perspective) and non-financial performance (includes learning and growth perspective, internal process perspective and customer perspective) (Figure 11) (Kaplan and Norton, 1992, 1993, 1996, 2001, 2006). Financial performance is reflected in measures, such as profitability and return on investment. While non-financial performance measures include labour efficiencies, customer satisfaction, quality improvements and business process efficiencies (Kaplan and Norton, 2006). The BSC is not just a financial and non-financial performance measure; it can also assist an organisation in setting and achieving long and short-term goals (Kaplan and Norton, 1996).

Figure 11 Balanced Scorecard



(Source: Kaplan and Norton, 2006)

The effectiveness of the BSC approach in practice is however, dependent on the information and technologies that organisations are using to support them in implementing a BSC (Davis and Albright, 2004). According to Jaklic et al. (2009), IS, such as BI systems, have started to have an impact on the *balanced set of organisational performance measures* (Chapman and Kihn, 2009; Popovič et al., 2018; Vallurupalli and Bose, 2018). This is because BI systems are expected to provide timely and efficient information that can be projected for management to monitor and improve both financial and non-financial performance. BI systems could improve the non-financial performance of the organisation as BI systems can turn data into actionable information. For example, the adoption of BI systems may help organisations in understanding customer profiles better, re-engineering internal business processes based on operational performance measures, and providing feedback and learning on employees' skills in the organisation. This might in turn, improve the strategic planning and budget processes in the organisation. For example, once management understands what their customers are buying, they can use this information to formulate their strategic objectives and set realistic targets. In addition, BI systems improve visibility of internal processes and make it possible to identify areas in need of improvement, which can be used to refine strategy on a continuous basis (Kallunki et al., 2011; Owusu, 2017). Thus, BI systems should promote improved non-financial performance. However, research that links BI systems and performance has focused mainly on financial performance, assuming that the improvement in financial performance is being influenced by the improvement in non-financial performance (Huang, 2009; Petrini and Pozzebon, 2009; Vallurupalli and Bose, 2018). This study explores these relationships in greater depth, including consideration of the intermediary role of management control systems.

4.3 Management Control Systems

Otley (2003) defined Management Control Systems (MCS) as systems that "monitor decisions throughout the organisation and guide employee behaviour in desirable ways to increase the chances that an organisation's objectives", "including organisational performance", will be achieved (Bhimani et al., 2008; Otley, 2003). The definition of MCS "includes planning systems", "reporting systems", and "monitoring procedures that are based on information use" (Chenhall, 2006). Kallunki et al. (2011), Hoque and James, (2000), Martin, 2020) and Davis and Albright (2004) stated that MCS can be categorised into formal and informal controls.

"Formal controls consist of contractual obligations and formal organisational mechanisms and can be subdivided into outcome and behaviour control mechanisms". Formal controls measure performance against expected outcomes and include budgetary controls, cost controls, activity-based costing, product costing and planning.

Informal controls are cultural and administrative controls relating to informal systems influencing organisational members and are based on mechanisms encouraging self-regulation (Otley, 1980; Chenhall, 2006; Chenhall, 2003; Smith, 2007). Examples of informal controls are personnel controls, governance structures, communications, policies, procedures, and social contracts (Chenhall, 2006). Through formal and informal controls, MCS promote a holistic view of the control environment in the organisation, i.e. as a “package” rather than as individual controls (Chenhall, 2003; Liew, 2019).

Previous research has focused mainly on formal controls such as planning, budgets, reward, and compensation (Simons, 1987; Chapman and Kihn, 2009). This is because informal controls are not easy to measure as they include values and beliefs. However, the adoption of BI systems may have impact on both formal and informal controls (Felício et al., 2021). In the case of formal controls, the impact emanates from the fact that some formal controls such as planning, budgets and techniques such as activity-based costing (ABC) are executed using the IS. BI systems may also make the monitoring of plans against actual performance easier as the required information can be displayed on a BI dashboard (Granlund, 2011). BI systems may support informal control by providing information to all employees that will encourage a culture of performance and the motivation to implement the strategy of the organisation. The monitoring of organisational performance may help align all the employees to work towards a common goal (Chapman and Kihn, 2009).

4.3.1 Previous Research on IS, MCS and Organisational Performance

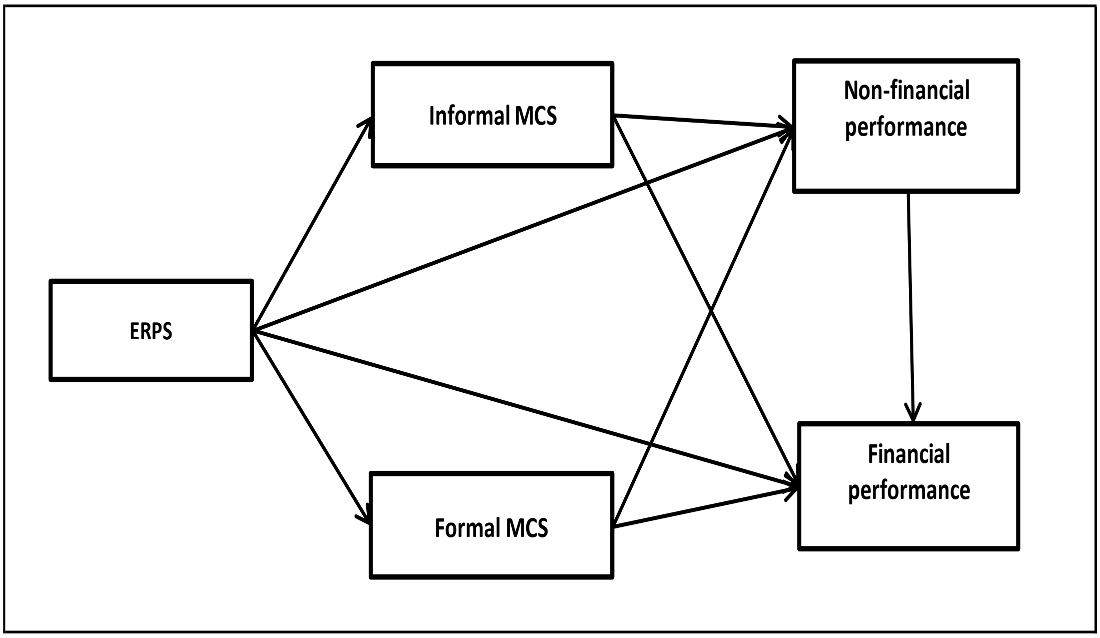
Previous research on organisational performance has indicated that information systems can impact organisational performance (Owusu, 2017; Vidgen, Shaw and Grant, 2017). There have been several findings obtained from this line of information systems research largely in terms of realising organisational benefits from IT implementation. However, results show positive, non-significant and negative relationships between IS and organisational performance (Chapman and Kihn, 2009; Kallunki et al., 2011; Hou, 2015; Shang and Seddon, 2002; Chapman, 2005; Ashrafi et al., 2019). The link between IS and organisational performance remains somewhat elusive (Liew, 2019).

Some prior researchers have taken the view that the link between IS systems, including BI systems, and organisational performance is best considered through the mediating effect of dynamic capabilities (Torres, Sidorova and Jones, 2018; Chen and Lin, 2021). Torres et al. (2018) contend that BI systems enhance the sensing and seizing capabilities of firms. Teece (2014) defined sensing capability as the organisation's "ability to identify and shape opportunities through the gathering and analysis of data" (Teece, 2014; Chen and Lin, 2021; Malmi et al., 2020). The seizing capability is defined by Torres et al. (2018) as the organisational ability to make decisions, "develop shared understanding among relevant stakeholders", and "formulate an action plan in response to identified opportunities" (Torres et al., 2018). By strengthening these capabilities, BI systems can then influence organisational performance through effects on other capabilities, such as business process change capability (Chen and Lin, 2021; Torres et al., 2018).

In addition, Aydiner et al. (2019) have taken a view that the link between BI systems and organisational performance can best be considered through the mediating effect of business process performance (Aydiner et al., 2019). Organisations can derive benefits from the increase in performance only if BI system adoption is aligned with the business processes and objectives of the organisations (Ramanathan et al., 2017). By improving organisational internal process efficiencies, BI system can improve financial performance (Aydiner et al., 2019).

Kallunki et al. (2011), take a different approach, and used the BSC approach in assessing the benefits for organisations of implementing an ERP system. They found that the implementation of the system has no direct impact on either financial or non-financial performance. Instead, the impact could only be realised when MCS performance was included as an intermediary between the IS and the financial and non-financial performance outcomes. Figure 12 is the research model developed by Kallunki et al. (2011) to test the ERP success model.

Figure 12 ERP Measurement Model



(Source: Kallunki et al., 2011)

This study adapts the above model (Figures 12) developed by Kallunki et al. (2011) to develop a research model for this study that examines the impact of BI systems in the organisational environment. However, the results obtained by Kallunki et al. (2011) in relation to ERP systems needs further consideration in the BI context. ERP systems are transactional systems and systems of record, while BI systems are management tools that combine multiple underlying transactional databases to provide a single integrated view with the aim of providing useful information to management for informed decision making. BI systems may thus influence performance dimensions differently to ERP systems.

Based on the literature reviewed, this is the first attempt to link BI systems to both financial and non-financial performance through consideration of MCS performance as an intermediary outcome of BI system use. There have however been past studies into BI and performance outcomes, along with other types of information systems, which have informed the direction of this study (Table 13).

Previous studies that investigated the adoption of BI systems generally support the notion that BI systems improve the financial performance of organisations (O'Brien and Kok, 2006; Williams and Williams, 2007; Pirttimäki et al., 2006; Vidgen et al., 2017; Aydiner et al., 2019).

The financial performance measures used were return on investment, net present value and return on assets. Hou (2015) however, argued that these financial measures used to measure the impact of transactional information systems (e.g., ERP) cannot be sufficient for assessing contemporary BI systems that offer multiple intangible benefits, including informed decision-making processes and improved user effectiveness. A more comprehensive approach in measuring organisational performance post the adoption of a BI system is warranted (Božič and Dimovski, 2019). Thus, the performance measures of interest should be a combination of internal business process, customers, learning and growth and financial performance, as suggested by the BSC. The balanced view is appropriate as the non-financial performance may also subsequently improve the financial performance (Hou, 2015). For example, improvements made in customer satisfaction can result in customer retention and repeat purchases that will have an impact on profitability. Furthermore, Wier, Hunton and Hassab Elnaby (2007) looked at the impact of non-financial performance on financial performance. They found that non-financial performance improves return on assets and stock returns. Financial performance is not limited on return on assets, but there are other indicators also (i.e., cost savings, profitability, revenue, and liquidity) that must be included to explain the full benefits of the adoption of BI systems (Wier et al., 2007; O'Brien and Kok, 2006; Vidgen et al., 2017).

Pirttimäki et al. (2006) attempted to use the BSC approach to study a BI system in a Finish Telecommunications company. The findings indicate that BI systems can contribute to improved learning and growth, internal business process, customer, and financial performance. They suggested that their measurement model can be tested in a practical environment to understand better the impact of BI systems on a balanced set of organisational performance outcomes (Pirttimäki et al., 2006; Lönnqvist and Pirttimäki, 2006; Olszak and Ziemba, 2003; Chen and Lin, 2021). Although their model proposed the inclusion of non-financial performance, it ignored other intermediary outcomes such as formal and informal MCS. Chapman (2005) and Chapman and Kihn (2009) argued that improved formal controls are an intermediary variable linking information systems to organisational performance. Their study indicated that the use of budgeting as a formal MCS was linked to perceived system success and suggest that BI systems can be useful to management even if it does not have a direct impact on financial performance. One of the reasons why the adoption of the system may not impact performance is due to the time lag between implementing the system and its performance effects. This is because the implementation of such a system is a long-term strategic investment and it takes a long time for these systems to influence the organisation.

However, Felício et al. (2021) confirmed that the inclusion of intermediaries can help trace the impact of systems, and specifically in their study, showed that formal MCS improved non-financial performance, and, in turn, non-financial performance improves financial performance.

The adoption of BI systems may have an incremental impact over existing MCS, and result in greater sophistication of MCS (Nadia, 2014). BI systems may improve MCS by supporting planning and forecasting capabilities to assist organisations in setting organisational objectives and assessing if organisational resources are being allocated correctly towards achieving organisational objectives (Hart and Snaddon, 2014). Furthermore, BI systems provide performance information of MCS (i.e., budget, variance analyse and performance report) to all levels of employees within the organisation and this may influence the behaviour of employees to implement organisational strategies. Liew (2019) argued that IS can improve communication among organisational units, “monitor and scrutinise employee work activities”, “thereby enabling MCS and monitoring of objectives including employee performance” (Liew, 2019). This thesis thus has an opportunity to expand on the work of Kallunki et al. (2011) by measuring the relationship between BI and formal and informal MCS and subsequent effects on both financial and non-financial performance (internal process, customer and learning and grow) variables. Inclusion of non-financial performance is important to provide the balanced view on organisational performance (Lin et al., 2009). Kaplan and Norton (1992) developed the BSC which includes non-financial performance measures i.e., internal business processes, customers, learning and growth, as additional elements to augment the financial performance. There have been several studies that recommend the use of BSC in measuring IT innovation’s (such as BI system, ERP) impact on organisational performance (Owusu, 2017; Pirttimäki et al., 2006; Lönnqvist and Pirttimäki, 2006). Examining the impact of BI systems on a *balanced* set of organisational performance measures will assist an organisation in justifying the decision made to invest in BI systems (Somers and Wong, 2010). Furthermore, the balanced performance measurement approach provides organisations an opportunity to better understand the ways in which BI systems can influence performance (Gorla et al., 2010).

Table 4 Organisational Performance Studies

Author(s)	Title	Methodology	Findings
O’Brien and Kok (2006)	“Business Intelligence and the telecommunication industry: can	Quantitative	BI system does improve profit.

Author(s)	Title	Methodology	Findings
	business intelligence lead to higher profit"?		
Olszak and Ziemba (2003)	"Business Intelligence as a Key to Management of an Enterprise"	Systematic review of literature	BI systems pose a chance for the effective management of an enterprise.
Lönnqvist and Pirttimäki (2006)	"The measurement of business intelligence"	Systematic review of literature	The balanced performance measurement could cover both BI process and important factors of process
Pirttimäki et al. (2006)	"Measurement of Business Intelligence in a Finnish Telecommunication company"	Case study	BI system can be measured using the Balanced scorecard performance.
Williams and Williams (2007)	"The Profit Impact of Business Intelligence"	Qualitative	BI driven profit can be achieved if top management is involved.
Wier et al. (2007)	"Enterprise resource planning systems and non-financial performance incentives: The joint impact on corporate performance"	Quantitative	Adoption of ERP through non-financial performance is likely to improve return on assets and stock returns.
Hart and Snaddon (2014)	"The Organisational Performance Impact of ERP Systems on Selected Companies"	Quantitative	Indicates a moderate improvement in customer, internal business process, financial and learning and development.
Elbashir et al. (2008)	"Measuring the effects of business intelligence systems: The relationship between business process and organisational performance"	Quantitative	The relationship between "business process performance and organisational performance" is moderate.
Kallunki et al. (2011)	"Impact of Enterprise Resource Planning Systems on Management Control Systems and Firm Performance"	Quantitative	ERP system has no influence on financial or non-financial performance, the influence is only through

Author(s)	**Title**	**Methodology**	**Findings**
			the intermediary formal control system.
Owusu (2017)	"Business Intelligence Systems and Bank Performance in Ghana: The Balanced Scorecard Approach"	Quantitative	BI system may improve customer, internal process, learning and growth but it does not impact financial performance.
Torres et al. (2018)	"Enabling Firm Performance Through Business Intelligence and Analytics: A Dynamic Capabilities Perspective"	Quantitative	BI systems can then influence organisational performance through effects on other capabilities, such as business process change capability.
Chen and Lin (2021)	"Business Intelligence Capabilities and Firm Performance: A Study in China"	Quantitative	BI systems can influence organisational performance through effects on other capabilities, such as business process change capability.
Aydiner et al. (2019)	"Business Analytics and Firm Performance: The Mediating Role of Business Process Performance"	Quantitative	Adoption of BI system through business process performance improves financial performance.
Ashrafi et al. (2019)	"The Role of Business Analytics Capabilities in Bolstering Firms' Agility and Performance"	Quantitative	BI systems improve firm agility through information quality and innovative capabilities, however the effects on "performance can vary by considering the moderating effect of environmental turbulence".

Author(s)	Title	Methodology	Findings
Felício et al. (2021)	"Adoption of Management Control Systems and Performance in Public Sector Organisations"	Quantitative	The study indicate how MCS are associated with the accomplishment of organisational objectives.
Liew (2019)	"Enhancing and enabling management control systems through information technology: The essential roles of internal transparency and global transparency"	Case study	The study indicate that IS can improve MCS thereby "enabling MCS and monitoring of objectives including employee performance".

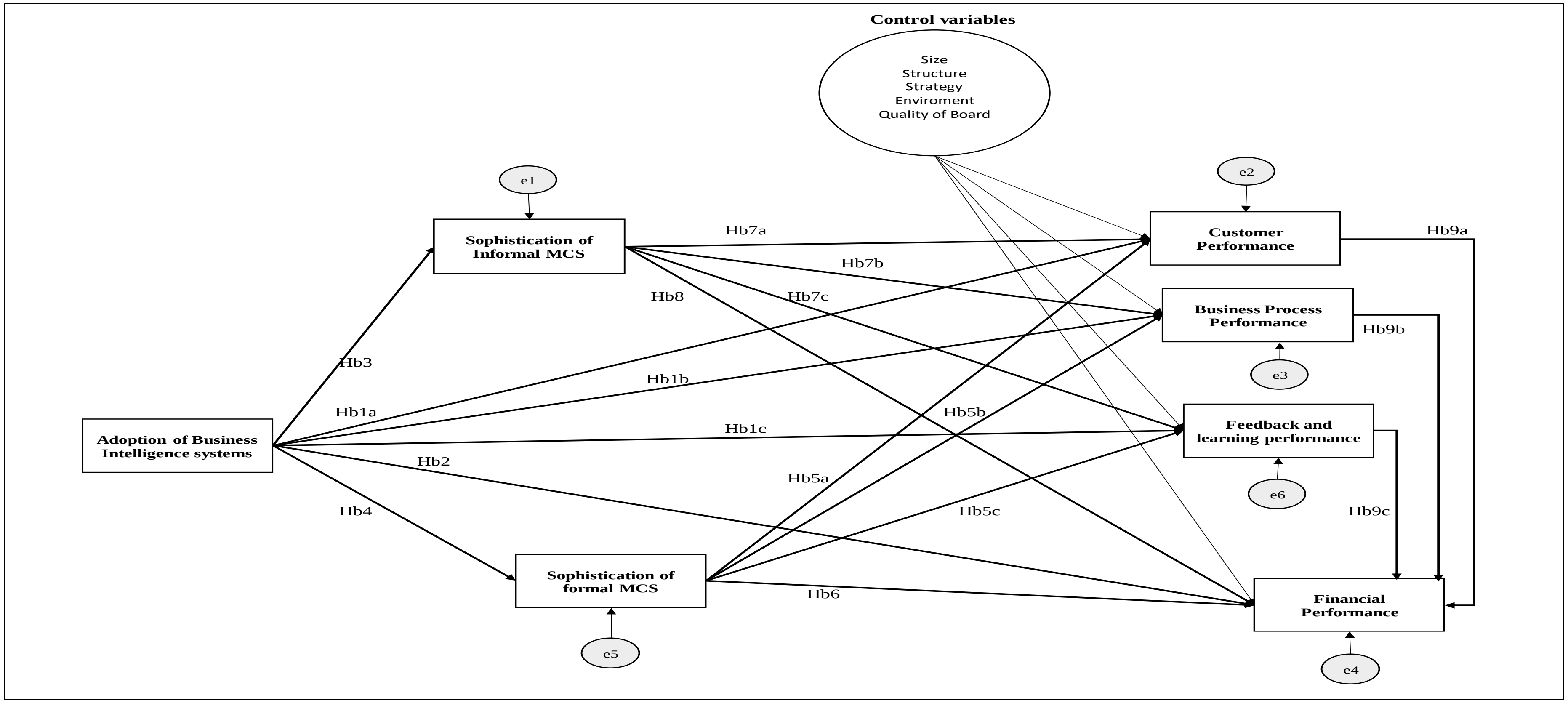
The development of the organisational research model and hypotheses to be tested are presented in the next section.

4.4 Research Model and Hypotheses

This research model proposed to address RQ3 is depicted in Figure 13. The development of the model has been influenced by the work of Kallunkuli et al. (2013) on the links between IS systems and MCS. It further draws on the BSC approach. The research model hypothesizes that the adoption and use of BI systems in the organisation has an impact on the sophistication of formal MCS and sophistication of informal MCS (Hb3 and Hb4). These MCS variables then impact organisational financial and non-financial performance (Hb5 through Hb8). The direct effect of BI systems on financial and non-financial performance is also depicted (Hb1 and Hb2). Non-financial performance may impact on financial performance (Hb9). The model also depicts a set of organisational factors that may moderate these relationships. These are discussed further below.

The adoption and use of BI systems at the organisational level is defined as the extent to which the BI system has diffused across organisational activities or processes, and its use routinized in organisational activities or processes (Liang et al., 2007). This concept of diffusion has been widely used as a basis for conceptualizing IS adoption and use at the organisation level (Cooper and Zmud, 1990; Rogers, 1965; Zmud and Apple, 1992).

Figure 13 Organisational BI Success Model



Adapted from Kallunki et al. (2011)

Hypotheses linking BI systems to sophistication of informal and formal controls are developed next, along with links to financial and non-financial performance. Thereafter, the link from sophistication of informal and formal controls to financial and non-financial performance is developed.

4.4.1 Impact of BI Systems on Non-financial Performance

Non-financial performance covers areas such as customer service, business process improvement, learning and development (Kaplan, 1992), and completes the holistic measurement of organisational performance (Hart and Snaddon, 2014). BI systems are expected to have a direct impact on the organisation's non-financial performance since BI systems are able to consolidate internal information (i.e., reports, productivity and efficiencies) with external information (i.e., customer satisfactions and performance of competitors) (Hart and Snaddon, 2014; Elbashir et al., 2008; CIMA, 2010; Cox, 2010; Ramanathan et al., 2017). The consolidation of external and internal information assists the organisation in monitoring organisational non-performance in areas such as process performance and customer service outcomes (Gauzelin and Bentz, 2017; CIMA, 2008).

To improve non-financial performance, organisations need to understand the behaviour of their customers towards the products or services they are offering (Kaplan, 2006). BI systems provide an opportunity for an organisation to be more customer oriented. Organisations with BI systems are better positioned to address customer queries and defects speedily as information can be made more rapidly available to management for decision making than in organisations without BI systems (Petrini and Pozzebon, 2009; Peters et al., 2016). Therefore, organisations with BI systems have real-time information available on customer queries and defects about products or services offered. Without monitoring customer queries and defects, organisations cannot make the type of decisions required to achieve full customer satisfaction and improve those processes which impact on performance (Cox, 2010; Aydiner et al., 2019). In addition, BI systems can assist organisations in monitoring the launching of the new products, create more value for customers and improve operational efficiencies and these are used to evaluate the learning and growth perspective in the organisations (Kallunki et al., 2011; Božič and Dimovski, 2019). A BI system also allows for monitoring of marketing campaigns, resources can then be allocated to the performing campaign to improve product visibility in the market. Employee development areas can be identified, and the necessary training and development can then be arranged (Hart and Snaddon, 2014; Gauzelin and Bentz, 2017). The

BI systems have a potential of cutting the time to prepare reports and reduce the personnel required to prepare reports. The personnel can then be re-deployed to other areas where they can add value (Kubina et al, 2015). BI systems can thus provide a more complete picture that assists management in evaluating the elements of non-financial performance and making better decisions, which result in improvement of non-financial performance (Kallunki et al., 2011). Therefore, it is hypothesised that:

Hb1. Organisational adoption of BI systems will have a positive direct impact on the organisation's non-financial performance.

4.4.2 Impact of BI Systems on Financial Performance

Financial performance is the measure that looks at the profitability of the organisation which can be measured through financial measures, such as net profit turnover, return on investment ratio, cash flow, sales growth, operating income, market share by segment, return on equity and liquidity ratio (Williams and Williams, 2007; Popovič et al., 2018). BI systems may provide for improved financial performance by allowing organisations to speed up decision making processes to stay ahead of competitors and improve their turnover (O'Brien and Kok, 2006). Decision making improvement offers greater returns as there is an opportunity *inter alia* of preventing wasted organisational resources from poor decisions. For example, the scenario planning functionality offered by a BI system may enable an organisation to set up more accurate selling prices and reduce headcount, thus leading to better profit margins (O'Brien and Kok, 2006; Aydiner et al., 2019), while predictive analytics offered by BI systems allow for dynamic forecasting to be performed, to predict products demand and lower production when demand is low to save on storage and distribution costs. The use of performance monitoring and dashboard reporting available on the BI system allows for actual expenditure monitoring against the set budget and reduces unnecessary costs (Olszak and Ziemba, 2012). The organisation can know on what they are spending and eliminate costs that might not add value on day-to-day running of the business. The reduction of costs may then improve the profitability as the organisation is able to control the outflow of cash. Therefore, it is hypothesised that:

Hb2. Organisational adoption of BI systems will have a positive direct impact on the organisation's financial performance.

4.4.3 Impact of Adopting BI Systems on Sophistication of MCS

MCS are the organisational systems, rules, practices, values, and financially quantifiable tools (i.e., budgeting, planning, costing and reporting) used to obtain employees to execute organisational strategy and achieve objectives (Simons, 1987; Di Vaio, Varriale and Trujillo, 2019). The sophistication of MCS is as an integrated management control used to inform planning, costing, and budgeting and to monitor the extent to which resources are used to achieve organisational objectives. The sophistication of MCS makes organisational performance information available to all employees within the organisation and this may encourage all employees to work towards achieving the planned organisational objectives (Martin, 2020).

The adoption of BI systems is expected to increase sophistication of MCS (Wier et al., 2007; Sageder and Feldbauer-durstmüller, 2019), for example, a BI system could provide information on the extent to which the production budget is met and make this information visible to all the employees within the organisation. Such visibility of information may encourage employees to work towards achieving the target without any management influencing them to do so (Granlund, 2011; Felício et al., 2021).

BI systems could integrate formal and informal controls. BI systems go beyond the traditional MCS (formal controls) which is about setting the targets (e.g., budget controls and standard cost) and incorporate beliefs, values, governance structure and policies and procedures (informal controls) (Grabski et al., 2011). Malmi and Brown (2008) stated that the use of formal controls alone does not provide a comprehensive picture of the organisational control environment. Formal controls are more reactionary than proactive as the decisions are taken after comparing actuals versus budgets (Nadia, 2014). The informal controls are more proactive as they may instil a certain organisational culture (e.g., culture of performance) (Rauhamäki, 2014). This will benefit the organisation in improving their MCS (Vakalfotis et al., 2011). It can be hypothesised that organisations in which BI systems are more diffused will have better informal MCS than those in which BI systems are less diffused, i.e., by analysing and making information on planning, budgeting, and performance more visible throughout the organisation, a BI system can provide for timely information that management can use to speed up decision making processes and monitor if the strategic objectives are being met (Nespeca and Chiucchi, 2018). Therefore, organisations with BI systems are expected to have better

MCS than those within which BI systems are absent or less well diffused (Granlund, 2011). Therefore, it is hypothesised that:

Hb3. Organisational adoption of BI systems will have a positive direct impact on sophistication of the organisation's informal controls.

Hb4. Organisational adoption of BI systems will have a positive direct impact on sophistication the organisation's formal controls.

4.4.4 Sophistication of MCS Influences Performance

A MCS comprises interdependent formal and informal controls that work together towards achieving a balanced set of organisational performance outcomes (financial and non-financial performance). Better MCS is expected to improve organisational performance. The sophistication of MCS is a system that managers use to influence others in the organisation to execute organisational strategy and improve organisational performance (Kallunki et al., 2011; Martin, 2020; Di Vaio et al., 2019). The sophistication of MCS may results in quality and production improvement in key business areas i.e., product reliability, customer service, product feedback and learning (Quattrone and Hopper, 2005; Liew, 2019). Better MCS may assist organisations in ensuring that organisational objectives are being met (Dechow and Mouritsen, 2005; Carenys, 2012; Laguir et al., 2019). MCS may improve financial performance by ensuring that organisations reduce the cost of manufacturing products/services through identifying inefficiencies with the production process and this may in turn, improve financial performance (Felício et al., 2021). Therefore, it is hypothesised that:

Hb5. Sophistication of an organisation's formal MCS will have a positive direct impact on its non-financial performance.

- Hb5a Sophistication of an organisation's formal MCS will have a positive direct impact on its customer performance.
- Hb5b Sophistication of an organisation's formal MCS will have a positive direct impact on its business process performance.
- Hb5c Sophistication of an organisation's formal MCS will have a positive direct impact on its feedback and learning performance.

Hb6. Sophistication of an organisation's formal MCS will have a positive direct impact on its financial performance.

Hb7. Sophistication of an organisation's informal MCS will have a positive direct impact on its non-financial performance.

- Hb7a Sophistication of an organisation's informal MCS will have a positive direct impact on its customer performance.
- Hb7b Sophistication of an organisation's informal MCS will have a positive direct impact on its business process performance.
- Hb7c Sophistication of an organisation's informal MCS will have a positive direct impact on its feedback and learning performance.

Hb8. Sophistication of an organisation's informal MCS will have a positive direct impact on its financial performance.

4.4.5 Impact of Non-financial Performance on Financial Performance

Non-financial performance includes customers, internal business processes and feedback learning and performance. Customers answer the question on how customers perceive the organisation. Customers can be categorised into four elements: lead time, quality, performance and service and cost (Kaplan and Norton, 2001). The organisation is expected to deliver customer products or services at a required lead-time, while maintaining the expected quality in improving customer performance and services at a reasonable cost. The delivery of customer services is dependent on existing internal business processes. Internal business processes are what the company should excel in (Kaplan and Norton, 1992; Caseiro and Coelho, 2019). The competencies that are critical to the success of an organisation and that are often used to measure internal business process performance include quality, cycle time, employee skills and productivity (Kaplan and Norton, 1996; Fink, Yogev and Even, 2017). There is a need for an organisation to continue to improve customer service and internal business process, and to use feedback learning and development to seek answers to questions on how the company can continue to improve and create value (Fink et al., 2017; Elbashir et al., 2021; Peters et al., 2016). Organisations should have the ability to monitor the launching of new products, creation of customer value and improvements in operational efficiencies (Kaplan and Norton, 2006).

Hou (2015) assessed how the usage of BI systems influence organisational performance in Taiwan's semi-conductor industry using the BSC approach and found that the use of a BI system improves financial performance indirectly through improvements in non-financial performance (internal processes, customer services and learning and growth). Similarly, Elbashir et al. (2008) measured the relationship between business processes and organisational performance. Their findings indicate that BI systems can improve internal business processes, which in turn, improves financial performance (Chen and Lin, 2021). Furthermore, Thompson (2004) argued that BI systems have a potential of improving customer performance and internal business processes through faster and more accurate reporting, which then translated to revenue growth and cost reductions. Similarly, Ritacco and Carver (2007) investigated a framework for measuring BI systems' value and claimed that BI systems can help improve non-financial performance outcomes such as increased customer retention, which translate to financial outcomes of improved revenue. Considering the above, it is reasonable to assume that the continued use of BI systems within South African organisations can improve their non-financial performance and in turn, their financial performance. Therefore, it is hypothesised that:

Hb9. Non-financial performance improvements due to BI will impact on financial performance.

- Hb9a Customer performance improvements due to BI will impact on financial performance.
- Hb9b Business process performance improvements due to BI will impact on financial performance.
- Hb9c Feedback and learning performance improvements due to BI will impact on financial performance.

4.4.6 Controls and Contingency Factors

The contingency variables can be traced back into the original structural contingency frameworks developed within organisational theory. Waterhouse and Tiessen (1978) and Otley (1980) conducted a review of theories and categorise the contingency variables as size[3],

[3] "Size refers to the structural property of the organisation and can be defined as sales volume, volume, net assets, customers, and number of employees".

structure[4], environment[5], culture[6], quality of the board [7]and strategy[8]. Anthony (1965) defines contingency as any variable that moderates the effects of an organisational characteristic on organisational outcomes. This would include outcomes such as MCS and performance. In the context of IS, the contingency approach underpins the view that there is no appropriate common IS that functions equally well when applied to organisations with different circumstances. It is suggested that the impact of BI systems on organisational outcomes, namely MCS and organisational performance, may be impacted by contingency factors such as environment, size, structure, strategy, quality of the board and culture (Ashrafi et al., 2019). The contingency concepts are also important when designing MCS to ensure that MCS meet user needs (Martin, 2020). Contingency theory assumes that the environment, internal and external factors, execution of strategy and size of the organisation, has an impact on the sophistication of MCS (Kihn, 2010).

Thus, as depicted in Figure 13, contingency factors that may impact on the links between BI systems and organisational performance and sophistication of MCS must be controlled in the analysis. These factors include environment, size, structure, strategy, quality of the board and culture. For example, larger organisations may prefer the sophistication of MCS brought about through BI systems for managers to influence employees in achieving organisational objectives. On the other hand, smaller organisations might be comfortable with less sophisticated MCS that have lower levels of IS support. In addition to size, other contingency factors may influence the BI systems to MCS relationship. For example, larger organisations with more complex structures might have more complex decision-making needs that require they integrate information from across numerous operations and therefore BI systems may be more important to the performance of such firms than simple organisations that have fewer operations (Lee and Widener, 2013). Organisations that encourage a culture of performance might require sophisticated MCS that require proper support of BI systems to achieve the desirable performance. It is therefore important to explain the improvement in sophistication of formal and informal controls brought about by BI systems through contingency variables (Ketokivi, 2006).

[4] "Organisational structure refers to the systems on how task allocations, co-ordination, supervisions are directed towards achieving organisational goals".
[5] "An organisations environment is defined as all the elements existing outside the boundary of the organisation that have the potential to affect all or part of the organisation".
[6] "Culture is the collection of values, expectations, and practices that guide and inform the actions of all team members".
[7] "A quality of the board is a balanced team with complementary skill sets and a culture that allows them to work together to make the most effective decisions for an organisation".
[8] "Strategy as competitive position", "deliberately choosing a different set of activities to deliver a unique mix of value".

The contingency variables are also used to explain the effects that the adoption of BI systems have on organisational performance. In larger organisations, or those operating in more complex competitive environments, there may be a greater need for BI systems to support more timely decision making, more variables to consider in decision making and more data to collate (Granlund et al., 2010). Therefore, BI systems are more likely to be of value to such firms than in others where the complexity of decision problems and information needs are lower. Therefore, it is likely that differential effects of BI adoption on organisational performance under different environment, culture, strategy, structure, and size conditions will be observed (Morton and Hu, 2008).

4.5 Conclusion

Research on the impact of BI systems on organisational performance is still surfacing. Prior research focused mainly on BI systems and financial performance without considering impacts on non-financial performance. However, it is necessary to understand the impact that BI systems have on both financial and non-financial performance of organisations. This chapter addressed that research problem by developing a research model linking the adoption of BI systems to a balanced set of organisational performance measures. Moreover, in the context of management accounting, one intermediary performance outcome of significance is the performance of the Management Control System (MCS). The implementation of BI systems is expected to improve the sophistication of formal and informal MCS. The research model developed in this chapter thus proposed that proper execution of MCS may subsequently result in the improvement of organisational performance.

This organisational level study of BI adoption makes a theoretical contribution by using the BSC approach to identify financial and non-financial performance outcomes and by examining improved MCS as an intermediary mechanism linking BI systems to financial and non-financial organisational performance. This will result in better understanding of a balanced set of performance impacts of BI systems from an organisational point of view.

In Chapter 5, the research methodology used to answer the three research questions of the research and test the associated research models and hypotheses as developed in Chapter 3 and 4, is discussed.

CHAPTER 5: RESEARCH METHODOLOGY

5.1 Introduction

In chapters 3 and 4, the study's research models and hypotheses were presented. This chapter defines the methodology used in gathering and analysing data to test the research models and thereby address the research objectives. The chapter outlines the research methodology with reference to the research focus, research approach, survey research strategy, data collection method, ethical considerations, research instruments, data analysis, reliability and validity and limitations and threats.

5.2 Research Focus

The study investigates the impact of BI systems at an individual and organisational level.

5.3 The Study of BI Systems at the Individual Level

Understanding the factors influencing the innovative use of the BI systems is critical in the management accounting context (Hou, 2012). It is also critical to understand the impact that innovative use of BI systems has on the individual performance of management accountants. To address RQ1 and RQ2 which is to examine the factors influencing the extent of innovative use of BI system among management accountants and the impact of innovative use of BI system on the individual performance of management accountants, Chapter 6 and 7 present the results of cross-sectional and longitudinal studies to explain the factors influencing the innovative use of BI systems and the impact that innovative use has on individual performance of management accountants. The motivation to adopt this context is because previous studies (Hou, 2012; Popovič et al., 2012; Hajri et al., 2014) did not distinguish between routine use and innovative use of the information system. Understanding factors influencing the innovative use of IS remains a research problem in need of investigation (Hou, 2012). The management accounting context provides a particular interest setting within which to investigate this question. This is because although investments in BI systems are often made with the aim of supporting management accounting functions, management accountants continue to work with organisational information and data outside of BI systems where they often prefer to process data in their individual spreadsheet systems (Granlund, 2011). The Delone and McLean (D&M) model was discussed in Chapter 3. The D&M model explains the variation of IS systems usage and the individual impacts of IS systems use (DeLone and McLean, 1992, 2003).

Hajri et al.'s (2014) work into innovative use of IS systems was also drawn upon in the development of the research model.

In addition, prior work (Wixom and Watson, 2010; Hou, 2012; Popovič et al., 2012) has not considered the dynamic nature of IS system innovative use and, whether early-stage of innovative use has an influence on late-stage innovative use, hence the use of longitudinal design has also been adopted. This should explain whether usage over time can improve individual performance of management accountants (Gorla, Somers and Wong, 2010). This is to address research RQ2, which considers the impact of innovative use of BI systems on individual performance of management accountants at a later point in time. To test the model, a longitudinal design research design is required. The testing of the model using the longitudinal design should allow for better examination of the implied causal linkages between the study's focal constructs (Courtois et al., 2014).

5.4 The Study of BI Systems at the Organisational level

It is necessary to extend the impacts of BI systems to organisational level outcomes – including the sophistication of management control systems (MCS) and a balanced set of organisational performance measures. To address RQ3, on the extent to which the organisational use of BI systems impacts on a balanced set of organisational performance measures both directly and indirectly through impacts on the sophistication of management control systems, Chapter 8 presents the results of a cross-sectional study to explain the impact that the adoption of BI systems has on a balanced set of performance (financial and non-financial performance) outcomes including the impact that MCS (formal and informal controls) have on financial and non-financial performance. The study addresses gaps left by prior studies (Hart and Snaddon, 2014; Gorla et al., 2010; Arnott, 2008) that researched the impact of BI systems on organisational performance but were focused on evaluating performance in the context of financial performance, such as profitability (e.g., return on assets, net profit, sales turnover and assets turnover) and ignored non-financial performance (O'Brien and Kok, 2006; William and Williams, 2007). It is however, important to evaluate the balanced view of performance as financial performance is only one of the aspects of a balanced view of performance measurement. Consequently, the role of BI systems in improving financial and non-financial organisational performance requires further attention (Azeroual and Theel, 2018). Examining this relationship will aid management in justifying the decisions that they have made in investing in BI systems (Azeroual and Theel, 2018).

The study also argues that an important intermediary performance outcome of BI systems is an improved organisational MCS. MCS (formal and informal controls) is concerned with the allocation, monitoring and co-ordination of organisational resources in order to assist managers in achieving organisational objectives (Granlund, 2011). The impact of using BI systems to support MCS is lacking. Prior studies (Quattrone and Hopper, 2005; Grabski et al., 2011; Kallunki et al., 2011) provide varied results while some argued that the adoption of BI systems resulted in the sophistication of MCS, but others have theorised that the use of IS systems had no impact on MCS (Vakalfotis et al., 2011; Grabski et al., 2011; Kallunki et al., 2011). Consequently, the relationship between organisational BI systems use and the sophistication of MCS is not well understood and the changes brought by BI systems on MCS require further attention (Vakalfotis et al., 2011). The sophistication of MCS may improve financial and non-financial performance (Kallunki et al., 2011; Quattrone and Hopper, 2005; Elbashir et al., 2013; Elbashir et al., 2011; Rom and Rohde, 2006). Furthermore, it has been argued that the role of contingency factors such as organisational strategy, size, environment, structure, quality of board and culture should be considered for their effects on the relationships between organisational BI systems use and organisational performance. The BSC framework which considers both financial and non-financial performance measurement was discussed in Chapter 4 (Kaplan and Norton, 1992), where hypotheses for the organisational level research model were developed.

The research design and approach used to test the individual and organisational level research models is discussed next.

5.5 Research Design and Approach

Research design is the plan to be followed in executing the research project. Overall, this study is informed by a philosophy consistent with positivism, premised on the assumption that objective reality can be expressed using causal relationships, and data to be collected can be measured reliably with a degree of accuracy (Cohen et al., 2007). This study reflects this positivist notion where the emphasis is on formulating an empirically testable theory to establish 'law-like' generalisations (Evans, 2010). In addition, the aim of positivist philosophy is to discover objective, physical and social reality by developing specific measures that detect dimensions of reality that interest the researcher (Cohen et al., 2007). Studies that adopt a positivist approach assume that the social world can be studied in the same way the natural world can be studied (Collis and Hussey, 2009). For the positivist researcher, one reality exists, and it is the duty of the researcher to establish that reality (Mertens, 2004). Generalisation to the population is made using statistical techniques on data gathered, such as through surveys or experiments (Saunders, Thornhill and Lewis, 2009).

Consistent with positivism, this research study follows a deductive approach and relies on theory to specify hypotheses and to eliminate alternative explanations for observations with the aim of strengthening causal inferences. Deductive research allows the development of conceptual and theoretical frameworks that can be tested through empirical observation (Saunders et al., 2009). A deductive approach is advantageous when there is a wealth of literature that can provide a theoretical framework from which hypotheses can be derived (Evans, 2010). In this approach, the researcher moves from theory to data in order to validate the framework (Collis and Hussey, 2009). The data to be collected is specific as identified by the theories.

A further consideration is the application of qualitative or quantitative approaches. Quantitative and qualitative approaches are complementary. The use of a quantitative approach is typically justified with reference to the similarity between social and natural phenomena, and that similar methods can thus be used to study both phenomena. Some, e.g., Ponterotto (2005), argue that the researcher should not be restricted to either quantitative or qualitative approaches but rather to consider the merits of each based on their characteristics and fit to the research objectives. Table 5 summarises these characteristics.

Table 5 Qualitative and Quantitative Research Methods

Characteristics	Qualitative	Quantitative
Research Objectives	"Unearthing and identification of new ideas", "thoughts", "feelings"; "preliminary insights on and understanding of ideas and objects".	"Validation of facts", "estimates", "relationships", "predictions".
Type of Research	"Normally exploratory designs".	"Descriptive and causal designs".
Type of Questions	"Open-ended", "semi-structured", "unstructured", "deep probing".	"Mostly structured".
Type of Execution	"Relatively short time frames".	"Usually significantly longer time frames".
Representativeness	"Small samples limited to the sampled respondents".	"Large samples", "normally good representation of target populations".
Type of Analyses	"Debriefing", "subjective", "content", "interpretive", "semiotic analyses".	"Statistical", "descriptive", "causal predictions and relationships".

Characteristics	Qualitative	Quantitative
Researcher Skills	“Interpersonal communications”, “observations”, “interpretive skills”.	“Scientific”, “statistical procedure translation skills”; “subjective interpretive skills”.
Generalisation of results	“Very limited”; “only preliminary insights and understanding”.	“Usually very good”; “inferences about facts”, “estimates of relationships”.

Source: (Summarised from Saunders et al., 2009)

This study has largely relied on the quantitative approach that deals with statistical, mathematical, or numerical analysis of data collected and is associated with the positivist research perspective. In addition, the quantitative research approach is also characterised by objective measurement, hypothesis testing, causality, and reproducibility (Collis and Hussey, 2009). Quantitative methods allow the collected data of this study to be subjected to various statistical analyses. The numeric data gathered and analysed quantitatively are used to generalise from the opinion of the particular groups of people studied to elaborate on the particular phenomenon under study (Ponterotto, 2005).

This study investigated the following:

- The factors influencing the innovative use of BI systems in the management accounting context;
- The impact of innovative use of BI systems on the individual performance of management accountants;
- The impact of organisational adoption of BI systems on organisational outcomes including the sophistication of MCS and a balanced set of organisational performance measures;

This study thus sought to establish relationships between variables and can thus be “termed” as “*explanatory research*” (Saunders et al., 2009). Explanatory research focuses on measuring causal relationships between the independent and the dependent variables. It explains how one variable can have an influence on another variable (Petty, Thomson and Graham, 2012). This research also required that one defines the measures, instruments, and sampling, along with the method of analysis before beginning data collection (Gong, Xu, and Yu, 2004).
As described in section 5.7.1 below, a small exploratory, qualitative study was conducted for the purpose of understanding and developing the construct of innovative BI usage. Exploratory research focuses on formulating problems more precisely, gaining insight, gathering

explanations, clarifying concepts, eliminating impractical ideas, and forming hypotheses (Evans, 2010). However, aside from the limited application of exploratory methods to gain more insight into BI usage, this work is largely defined as deductive, quantitative, and explanatory.

5.6 Research Strategy and Time Horizons

The research strategy adopted for this deductive, quantitative, and explanatory study is a survey. The survey is frequently used in deductive studies within commercial and management disciplines to provide an answer to questions such as what, how much and how many (Petty et al., 2012). The survey research strategy for explanatory research can also ensure greater confidence in the generalisation of the findings as it can facilitate the collection of data from a large representative sample (Gong et al., 2004).

Surveys can be cross-sectional or longitudinal. To address RQ1 and RQ2, which are focused on the individual use and impact of BI systems, a longitudinal design was adopted. Here, data was collected from the sample over three periods (waves) approximately 12 weeks apart. The data of Wave 1 was used to test the complete cross-sectional model, while data from waves 2 and 3 allowed for the test of the hypothesized cross-lagged models. Conducting a study at three different waves can assists researchers to establish better temporal precedence in the data (Petty et al., 2012), and to reduce common method bias associated with cross-sectional designs. The common methods bias present in observed relationships is reduced when data used to examine relationships has been collected at different time periods and on different survey instruments (Cohen et al., 2007), such as when testing the effects of IS user satisfaction on IS use.

For RQ3 focused on the organisational-level use and impact of BI systems, this study adopts a survey strategy with a cross-sectional time horizon. In the cross-sectional design, data is collected once, at a single point in time from the sample of the population units (Ponterotto, 2005).

5.7 Data Collection Methods

The survey method provides an opportunity to the researcher to collect data in an effective and economical way (Cohen et al., 2007). Survey methods facilitate the collection of data from larger sample sizes. In order to produce meaningful results surveys, they need to follow defined procedures (Collis and Hussey, 2009). The following sections further discuss the data collection carried out at the individual level and at the organisational level. First, sampling is discussed.

5.8 Sampling Strategy for Surveys to Study Individual Use and Impact of BI Systems (RQ1 and RQ2)

A survey can be conducted either through sample surveys or census surveys (Evans, 2010). Sample surveys are used to collect data from a representative subset of a population. On the other hand, in census surveys, the collection of data includes the whole population (Salkind, 2009). Sampling is the method used to identify the members of the population to be studied. There are two main sampling methods. These are "probability and non-probability sampling". Probability sampling gives an equal opportunity to all members of the population to be sampled using a random sample (Evans, 2010). Results can be produced that represent the population, then the probability sampling such as simply random, systematic, stratified, cluster sampling can be used. While non-probability sampling is a sampling technique that the researcher selects the sample using subjective judgement rather than random selection (Salkind, 2009). A non-probability sample includes convenience, judgement, and snowball sampling. In considering the sampling method, it is important to focus only on the individuals or organisations that are using the focal technology (Gyampah and Salam, 2004).

In addressing the RQ1 and RQ2 of this study, data was collected by means of a sample survey of selected individual management accountants over the three-time waves (W_1, W_2 and W_3). Therefore, data collection was restricted to individual management accountants using BI systems as part of their work. This required the sampling of management accountants from South African organisations that have already implemented a BI system for active use (Elbashir et al., 2013). The selection of these organisations was based on judgement and the following rationale. There are five large BI vendors in South Africa that are currently being used by organisations (Gartner, 2015). Gartner (2015) listed the large BI vendors and their market share as follows:

- SAP 23% market share
- Oracle 16% market share
- SAS 13% market share
- IBM 12% market share
- Microsoft 9% market share
- Other vendors 27% market share

The large BI vendors have 73% market share, and the other small BI vendors have 27% of the remaining market share. The Financial Mail (2016) ranked the largest leading companies using their total assets value and identified 200 leading companies in South Africa. SAP (2015) indicates that BI has already diffused widely into top companies. The largest 200 companies listed by Financial Mail (2016) were chosen as part of the sampling frame for the purpose of the individual level study. The largest top 200 companies include sectors such as financial, manufacturing and telecommunications, among others.

In addition to the top 200 leading companies in South Africa, 196 public entities were also sampled. These are mainly national public entities which are schedule 2, 3A and 3B companies, as listed by National Treasury (PFMA, 1999). The total number of organisations sampled was thus 396. CIMA (2010) stated that both public and private sector have already diffused BI systems widely. The use of BI systems can assist the private and public sector in economic growth and competitiveness in all economies (Maldifassi and Crovetto, 2013). This means that countries should focus on encouraging both the private and public sector to continue using the BI system (SAP, 2015). The list of these organisations and contact details were obtained from the Financial Mail Annual Report, Public Financial Management Act (PFMA) and Integrated Annual Reports. The organisations were contacted individually to obtain contact details of the management accountants who could be invited as potential respondents.

The first wave (W_1) survey was to obtain respondents' perceptions of BI systems, information, data and service quality, their satisfaction with the BI system, their routine and innovative use of the BI, their task complexity, self-reported individual performance, as well as their self-efficacy and other relevant demographics. This has provided a cross-sectional test of the full research model (Figure 6). The second and third waves (W_2 and W_3) survey has been used to obtain data on users on-going system perceptions and levels of satisfaction, routine and innovative use of BI systems, and individual performance. This was used for a longitudinal test of the research model and allowed for better temporal precedence to be established in the data. For waves (W_2 and W_3) only management accountants who have been using their organisational BI system for less than two years were targeted. This is because in the IS usage context, less than two years was considered in Al-Mashari (2001) as a reasonable period for an organisation to still be in the stabilisation and learning stage of new IS innovation. In addition, there is still an opportunity for an organisations and individuals to improve the usage of the IS.

The 396 organisations were contacted telephonically and through emails to establish the number of years they have been using BI systems. Gyampah and Salam (2004) state that the companies that had implemented information system for two years or less are regarded as late adopters of the technology. The number of years that a company has been using an information system also has an impact on the use of information systems by individual employees such as management accountants. Therefore, the number of years that an organisation has been using the information system can also be a representative of individual use (Gartner. 2015). W_1 included all the individual management accountants using their organisation's BI system. Their data provided for a cross-sectional test of the full research model. The individual management accountants whose organisations had been using BI for more than two years were not considered for W_2 and W_3. Only the individual management accountants whose organisations had been using BI system for two years and less were surveyed in W_2 and W_3 for the longitudinal test of the research model.

For each organisation, a key contact person was identified who provided permission for their organisation's management accountants to take part in the study and contact details of the potential respondents were also obtained from the key contact person, the invitation to participate was distributed directly to the management accountants. Efforts were made to invite as many individual management accountants as possible to take part in the study; however, there was a substantial attrition over W2 and W3 as anticipated, which is, unfortunately, a common phenomenon in multiple-wave longitudinal studies (Courtois et al., 2014).

A minimum of 1000 individual management accountants were selected from the 396 largest organisations using the BI system. The range was a minimum of one management accountant in some organisations up to a maximum of 15 in the largest firm, with an average of five management accountants per organisation. "*The determination of the final sample size involved judgement as well as calculation*" (Awang, Afthanorhan and Asri, 2015). The "determination of a sample size was a subjective", "intuitive judgement made by the researcher based on past studies" (Sedera and Gable, 2004). Table 6 offers examples of prior studies used as the basis for the selection of the sample size.

Table 6 Examples of Previous Studies

Scope of the study	Sample used	Data analysis	Authors
Understanding consumer's intention	700 (response rate 56%)	SEM	(Chen and Cheng, 2009)
Post adoption of information technology use	800 (response rate 43%)	SEM	(Ahuja and Thatcher, 2005)
Student acceptance of tablet devices	678 (response rate 49%)	SEM	(Courtois et al., 2014)
Measuring KMS success	500 (response rate 58%)	SEM	(Wu, 2006)
Impact of BI system on performance	500 (response rate 11%)	SEM (PLS)	(Wierder and Ossimitz, 2015)
Individual innovative use of IS	1000 (response rate 51%)	SEM (PLS)	(Hajri et al., 2014)

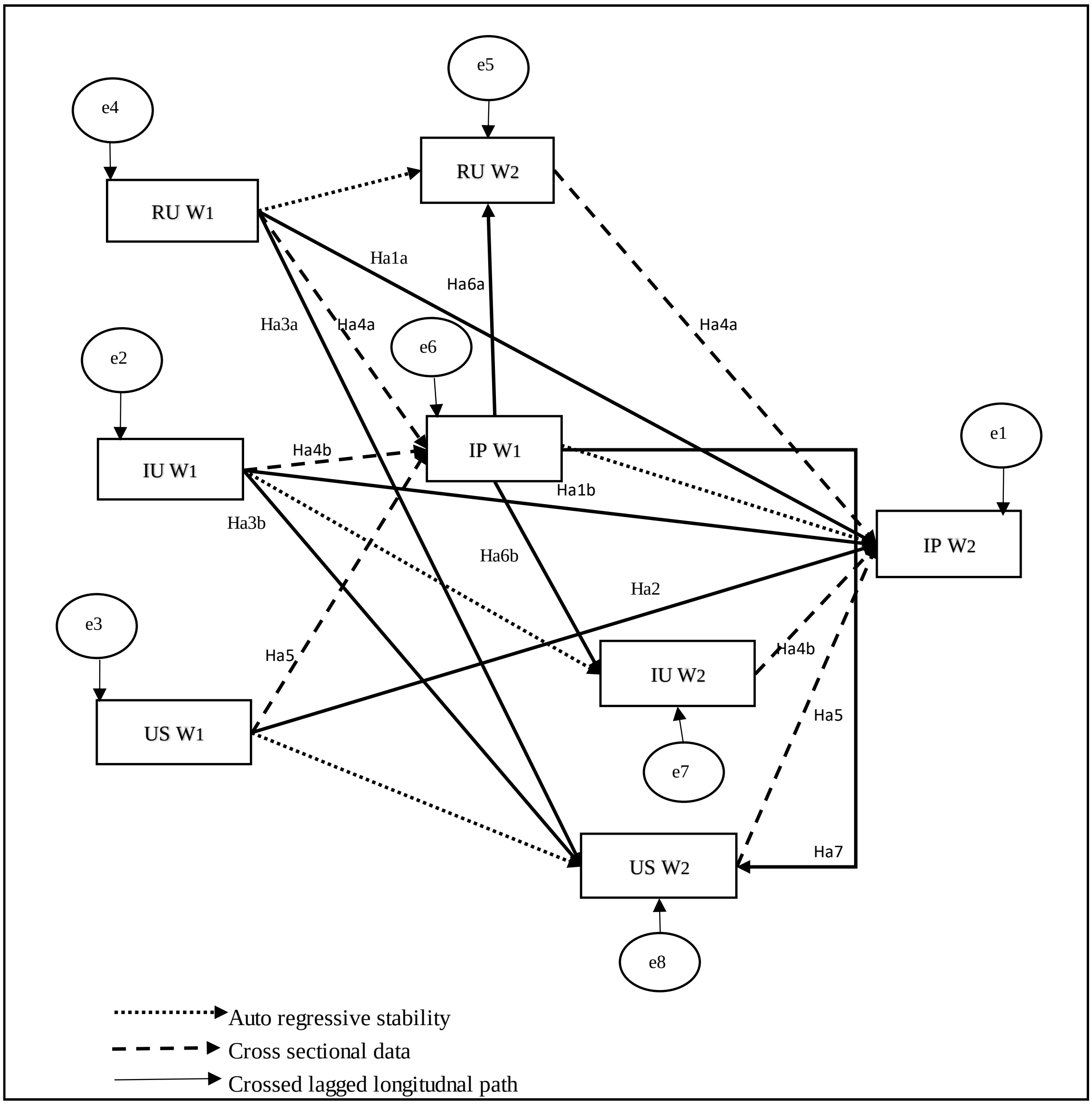
Although the previous studies (Chen and Cheng, 2009; Hajri et al., 2014) were used in determining the sampling size, the following was considered; "number of groups within the sample", "the value of the information and the accuracy required of the results", "the cost of sampling and the variability of the population" (Collis and Hussey, 2009). The sample size of 1000 used in this study is consistent with those used in previous studies as indicated in Table 6.

Wave 1 gathered perceptions from the sampled management accountants on all the variables in the research model (Figure 6), namely, system quality, data quality, information quality and service quality, as well as user satisfaction, routine and innovative use of the BI system, their task complexity and self-reported individual performance, as well as their self-efficacy and other relevant demographics. W_1 provided for a cross-sectional test of the full research model.

The second round of data collection took place after three months. However, only a sub-sample of users from those organisations within which BI systems have been available for less than two years were invited to participate. This was because in the IS usage context, less than two years was considered in Al-Mashari (2001) as a reasonable period for an organisation to still be in the stabilisation and learning stage of new IS innovation. There is still an opportunity for any organisations and individuals to improve the usage of the IS. At this point, the BI systems had been used daily for decision making and the preparation of daily and monthly reports. This wave was focused at capturing on-going experiences of routine use, innovative use, user satisfaction and individual performance behaviour. Lastly, a third wave was administered after a further four months of interaction with the BI system. At this stage, the individual management accountants have on-going experience in using BI system in that financial year, for decision making and preparation monthly and half-yearly reports against which to evaluate the individual performance impacts along with perceptions of satisfaction and usage behaviour. BI systems are used with the aim of improving innovative use, user satisfaction and individual performance, thus collection of data on these variables across the time waves was appropriate. The total time interval selected was seven months. This is because in the IS usage context, seven months was considered in Gong et al. (2004) as being a good compromise for a period for longitudinal usage studies.

Although wave 1 data still provided for a cross-sectional test of the model, the collection of wave 2 and wave 3 data provided for a series of longitudinal cross-lagged models to be tested (Figure 14). The detailed longitudinal cross-lagged model tested was discussed in Chapter 3.

Figure 14 Example of Longitudinal Model



Source: Researcher's Own

The questionnaires distributed have been administered electronically. The email invitations were sent directly to the potential respondents with a cover letter/participant information sheet inviting them to participate, and if they chose to participate, they clicked on a link to the online questionnaire. "The longitudinal study required that data from respondents be matched over time for comparison and analysis". Therefore, "identification of the respondents was essential at each time point so that data from the same respondents could be matched". Because responses were completed anonymously, matching was achieved in this study through the use of self-generated identification codes. This permitted an anonymous means to track respondents over multiple data collection points (Yurek, Vasey and Havens, 2008). These were only necessary to include the instruments to firms where the BI systems were in use for less than two years, and was not necessary for those where use was greater than two years, as those respondents were not invited for subsequent waves.

Refer to “Appendix A”, “Appendix B” and “Appendix C” for cover letter on instructions letters or participants information sheet.

5.9 Sampling Strategy for Surveys to Study Impacts of BI Systems at an Organisational Level (RQ3)

In addressing RQ3 relating to the impact of BI systems on organisational outcomes, data was required on organisational level BI adoption, a balanced set of organisational performance measures, the sophistication of “Management Control Systems” (MCS), and contingency factors.

For the organisational level study, the same Financial Mail (2016) top 200 companies and 196 public entities were sampled. The total number of organisations that were part of the sampling frame of the organisational study was thus 396, this included both the private (n=200) and public sector (n=196). In measuring the impact of BI systems, it was considered important to focus on both public and private organisations. This would provide a balanced view of the impact of BI systems on organisational performance.

The 396 organisations were selected because they operate in competitive or resource constrained settings and for them to perform successfully, BI systems are needed to assist in decision making. Therefore, these organisations are likely to have implemented BI systems (SAP, 2015). It is important to include public and private sectors in research as improving organisational performance in both sectors is necessary (Maldifassi and Crovetto, 2013). The sharing of best practice across public and private companies helps in addressing their respective challenges and opportunities (Agolla and Van Lill, 2013). It is for these reasons that the public sector was included with private sector firms in the sample.

Within organisational level studies that make use of survey methods, there is a need to consider appropriate key informants who can provide data about the organisation. Executives are the most frequently identified key informants. There is, however, an argument on whether data collected in surveys from individual executive respondents measures the organisation or individual perception (Sedera and Gable, 2004). Gong et al. (2004) argue that executives within organisations have the ability to provide organisational perception on variables such as performance as they drive organisational strategies and have organisational interests at heart. The impact of BI systems on organisational performance is considered a strategic level problem. Therefore, selecting key executives as informants for each of the 396 sampled organisations provided a relevant organisational perception (Ponterotto, 2005). The executives selected included but were not limited to Chief Financial officer (CFO), Head of management accounting, or equivalent, CEO and other C-suite Executives.

The lists of executives were obtained from the organisational annual report and website. The invitation to participate was distributed directly to the respective executive's office. Efforts were made to invite as many executives as possible to participate in the study. However, the invitation was limited to one executive per organisation. It was understood that most of the respondents have a busy work schedule. A reminder email was sent after two weeks. In some cases (nine respondents), face-to-face administration of the survey took place due to respondents' request, and in other cases (14 respondents), a telephonic administration of the survey took place.

5.10 Ethical Clearance

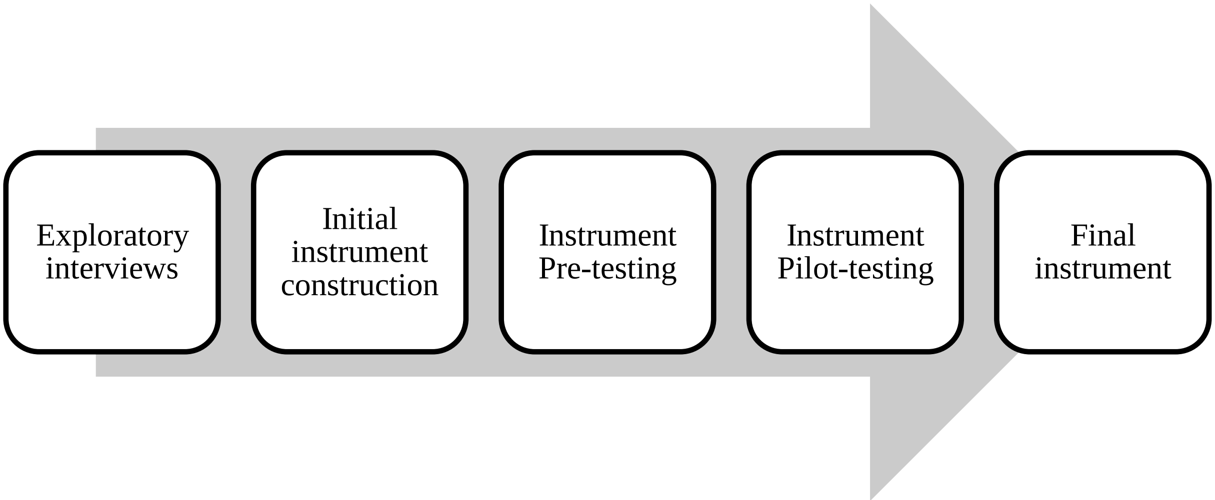
The researcher needed to anticipate ethical issues before the study could be conducted (Gong et al., 2004). The essential "purpose of research ethics is to protect the welfare of research participants and extends further into areas such as scientific misconduct and plagiarism" (Byrne, 2013).

Prior to the commencement of data collection, ethics clearance from the "Human Research Ethics Committee (Non-Medical) office at the University of the Witwatersrand", "Johannesburg was unconditionally approved". Protocol number is H17/04/22 (Appendix F). The researcher agreed to abide by the "ethical clearance" issued by the "Ethics Committee" of the "University of the Witwatersrand". "This was to ensure that the researcher abided by institutional ethical guidelines pertaining to research on human respondents". "The participation of respondents in the study was completely voluntary", and "confidentiality or anonymity was guaranteed". Respondents were informed that data collected would not be shared with any other party and would be destroyed on completion of the research project. The respondents were informed by the researcher that the data to be collected from the on-line electronic questionnaire and interviews was confidential and the results of the questionnaire and the interviews would be reported in the aggregate and not as the views of individual participants. The researcher instructed respondents not to fill in their personal or companies' details, so that anonymity could be guaranteed. Participants were also informed that information collected would only be used for the purpose of the research and the final report would be made available to the organisation on request. The safety of the respondents was also assured during the data collection process. The respondents filled in the questionnaires on a voluntary basis and could refuse to answer certain questions or withdraw from the study at any stage.

5.11 Instrumentation Construction and Measures for Individual Study

Construction of the instrument for the study of BI at the individual level followed the following steps (Figure 15):

Figure 15 Instrument Construction for Individual Study



5.12 Exploratory Interviews

RQ1 and RQ2 is focused on individual use of BI systems. Because the constructs of BI use (routine and innovative use) are under-developed in the literature, initial exploratory interviews were conducted with six BI system practitioners and academics experts. These six individuals were selected for their experience and to explore with them how they understand and/or engage in routine versus innovative BI use. Interviews were held with them individually and they were asked standard questions on their understanding of BI systems and the capabilities of BI systems (Appendix E). The results were interpreted in conjunction with existing literature (Popovič et al., 2012; Hajri et al., 2014). It was determined that innovative BI use could be understood primarily as the choice of individuals to use more advanced BI system features such as self-service tools, interactive visualization, predictive analytics, and drill down functionality to support their work, while routine use occurs when users use BI systems to extract pre-built reports only, but without using the more analytical features of BI systems. A summary of the results of exploratory interviews into BI use is presented in Table 7.

Table 7 Summary of the Results of Exploratory Interviews

Expert Interviewee	Innovative use	Routine use
Interviewee 1	Advanced use of BI system is the use of all the features on BI system in supporting performance (i.e., self-help, predictive analytics, and optimization).	The use of certain features of BI system without considering other features that are important (i.e., abstracting data in BI and use Excel to report)
Interviewee 2	BI system is designed to handle complex data to resolve business reporting problems. BI system in an advanced technology by nature (i.e., Future prediction, 'what if' scenario and Scorecard).	It is the use of BI system to draw standard report and data
Interviewee 3	Advanced use of BI system is the use of all features of BI system by organisations (i.e., interactive visualisation, dashboard, and key performance target).	Routine use is the use of some feature of BI system, particularly standard reporting, and abstraction of data.
Interviewee 4	Advanced use allow BI systems can present information in various graphics and images. This makes management understand performance better (i.e., interactive visualization, scenario planning, agile visualisation, trends analysis and drill-down).	Routine use of BI system is only the use of basic functionalities (i.e., standard reports, raw data, running existing queries).
Interviewee 5	Advanced use allows the use of BI system to handle various complex scenarios and reporting using different assumptions (i.e., advanced forecasting, modelling; performance reporting, dashboard, and agile visualisation)	Routine used is dependent on organisational maturity (i.e., standard reports are used at an early-stage of implementation)
Interviewee 6	Advanced use is the use of BI system to abstract past data and current data	It is the use of BI system to run existing reports only without

Expert Interviewee	Innovative use	Routine use
	to predict future performance (i.e., the past sales performance can be used to predict the future sales performance of the organisation)	developing personalised reports or queries.

5.13 Initial Instrument Construction

In addressing RQ1 and RQ2, the research model (Figure 6) on individual innovative use of the BI systems is comprised of seven core constructs, namely system quality, data quality, information quality: service quality, routine use, innovative use, user satisfaction and individual performance. Additional variables included task complexity, self-efficacy, user experience and education, among other controls. Table 8 below presents example items and literature sources for each construct. The detailed measures are listed in “Appendix A”, “Appendix B” and “Appendix C”. Except for demographics, most constructs were measured using multi-item Likert scales (“1=strongly disagree” to “7=strongly agree”), with the exception of routine and innovative use that were “measured using 6-point scales” (“1=never” to “6=very often”), as illustrated in “Appendix A”, “Appendix B” and “Appendix C”. The research instruments were adopted from the work of DeLone and McLean (2003) as well as Hou (2012), Wu (2006), Popovic et al. (2012) and Hajri et al. (2014). In addition, the routine and innovative use instruments were enhanced through the interviews conducted with the experts, as described above. The instrument included a filter question to ensure that only management accountants who are using the BI systems were respondents to the survey.

Table 8 Operationalization of Constructs to Examine Individual Use and Impact

Variable	Conceptual Definition	Example Questionnaire Item	Number of items	Literature Source(s)
***System Quality**	System quality refers to the characteristics of a system as experienced by its user such as its usability, availability, reliability, and response time.	The BI system is easy to navigate	6	System quality was measured using six items (DeLone and McLean, 1992, 2003). These items measure the usability, reliability, and response time of the BI systems.

Variable	Conceptual Definition	Example Questionnaire Item	Number of items	Literature Source(s)
***Data Quality**	Data quality refers to the unprocessed data records that are stored within the computer system and are considered complete and accurate to be used for planning and decision making	Data inputs records in the system are always complete	3	System quality was measured using three items (Hou, 2012; Wu, 2006). These items measure the integrity of data on the BI systems.
***Information Quality**	Information quality refers to the characteristics of the information output of the system such as its perceived accuracy, usefulness, relevance, completeness, and understandability.	Information output by the BI system is presented in a useful format	7	Information quality was measured using seven items (DeLone and McLean, 1992, 2003). These items measured the quality, usefulness, relevance of the information output of the BI systems.
***Service quality**	The support that the user receives to make more effective use of the BI system.	My organisation's BI support team is always helpful to me	5	Service quality was measured using five items (DeLone and McLean, 1992, 2003). These items measured the support services that the users received while using the BI systems.
****Innovative use**	Innovative use refers to how regularly a user makes use of more advanced BI system features such as self-service tools, interactive visualization, predictive analytics reports and drill down functionality to support their work	I regularly use more advanced features of the BI tool such as: Self-service tools	12	Innovative use was measured using 12 items (Popovič et al., 2012; Hajri et al., 2014). These items measured how the individual users used the innovative features of the BI systems.
***Self-efficacy for innovative use**	refers to an "individual's belief in his or her capacity to execute behaviours	I could use more advanced features of a BI tool with	3	Self-efficacy for innovative use was measured using

Variable	Conceptual Definition	Example Questionnaire Item	Number of items	Literature Source(s)
	necessary to produce specific performance attainments”	only the built-in help functions for assistance.		three items (Popovič et al., 2012; Hajri et al., 2014). These items measured the individual belief that was necessary to produce specific performance attainments.
****Routine use**	Routine use occurs when users use BI systems to extract pre-defined reports only but without using customized analytical features of BI systems	I use the BI system on a regular basis. Over the past months I have often used the following basic functions of BI tools: Running existing reports	8	Routine use was measured using eight items (Popovič et al., 2012; Hajri et al., 2014). These items measured how the individual users used the routine features of the BI systems.
***User satisfaction**	User satisfaction refers to the way in which the user feels about the IS	I enjoy using the BI system	5	User satisfaction was measured using five items (Hou, 2012; Wu, 2006). These items measured the way in which the individual user felt about the BI systems.
***Task complexity**	“Task complexity has been recognized as an important task characteristic that influences and predicts human performance and behaviours”	BI system provides the information needed to perform my tasks	4	Task complexity was measured using four items (Popovič et al., 2010). These items measured the task characteristics that influenced individual performance and behaviours.

Variable	Conceptual Definition	Example Questionnaire Item	Number of items	Literature Source(s)
***Individual performance**	Individual performance is defined as the job-related activities assigned to employee and the extent in which those activities are executed by an individual	Using the BI system increases my work productivity	7	Individual performance was measured using seven items (Hou, 2012; Igbaria and Tan,1997). These items measured the job performance executed by individuals.
	* "All items measured on a Likert scale from 1=Strongly Disagree to 7=Strongly Agree" ** "All items measured on a Likert scale from 1=Never to 6=Very often"			

5.14 Pre- and Pilot Testing of the Questionnaires

In identifying and developing the measures, prior literature was used to ensure content validity. Content validity refers to the extent in which the measure represents all aspects of a construct. Furthermore, pre-testing was conducted using ten BI system practitioners and academic experts who reviewed the instrument. The recommendations from these experts and practitioners were used to enhance the content validity of the instruments. The recommendation of the experts included the extension of routine use instruments by adding data cleansing and executing existing queries. While on innovative use instruments, the following were added: optimisation, agile visualisation, and interactive visualisation. Furthermore, chart of accounts was removed from routine use instruments as this was not part of the features of the BI systems.

Thereafter, "pilot testing was conducted to determine if the survey was understandable for participants and whether there were any ambiguous or confusing measurement items in the questionnaire, as well as to ensure that the survey items were appropriate to individual users of BI systems". This was to ensure the "face validity" of the instruments. The pilot test was carried out using a convenience sample of 20 management accountants who were BI users and were drawn from the same population as the main study. The individuals sampled to participate in the pilot study were not the same individuals who reviewed the instruments initially. Their responses helped to determine the face validity of the measures and allowed for some initial screening of the descriptive statistics of each scale, including variation in responses, uni-dimensionality, and overall scale reliability measures. The individual performance instrument had eight items to be measured, one item was dropped (IP7), while system quality had seven items to be measured, one item was dropped (SQ3). These items were dropped because the item loading was less than 0.50.

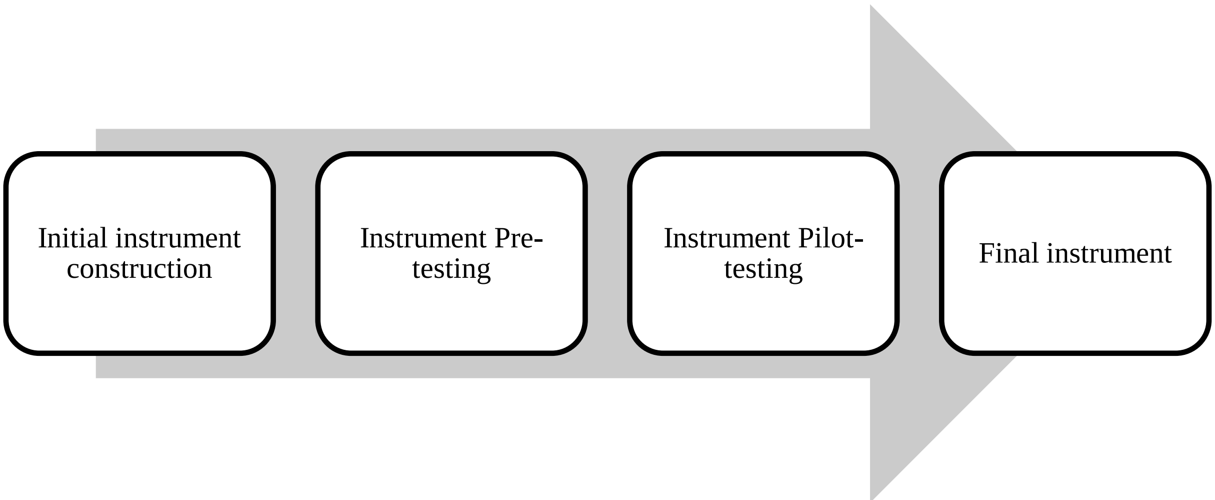
5.15 Final Instrument Administration

The final questionnaire for the individual level study (refer Appendix A, B and C) was administered electronically to the sample described in section 5.5.1. The questionnaires were distributed through the emails directly to the respondents; in some cases, they were sent to the key contact person who then forwarded the instruments to the respondents with a cover letter/participant information sheet inviting them to participate, and if they chose to participate, they could click on a link to an online questionnaire. Reminder emails were sent after two weeks of sending the instruments to improve the response rate. All respondents were sent a reminder.

5.16 Instrument Construction for Organisational Study

Construction of the instrument for the study of BI at the organisational level followed the following steps (Figure 16):

Figure 16 Instrument Construction for Organisational Study



5.17 Initial Instrument Construction

The research model (Figure 13) hypothesizing the impact of BI systems adoption on organisational performance is comprised of five core constructs, namely, organisational level adoption of BI system, non-financial performance, financial performance, sophistication of MCS formal controls, sophistication of MCS informal controls, together with the selected contingency variables. The operationalization of these constructs is highlighted in Table 9 and detailed in Appendix D. The items measuring organisational performance and sophistication of MCS were adopted mainly from the work of Kallunki et al. (2013). Except for data on organisation characteristics, all constructs were measured using 7-point multi-item Likert scales as illustrated in the Appendix D.

Table 9 Operationalization of Constructs to Examine Organisational Use and Impact

Variable	Conceptual Definition	Example Questionnaire Item*	Number of items	Literature Source(s)
***Adoption of BI systems**	Organisational level adoption is "defined as an organisational effort directed toward diffusing appropriate information technology within a user community", which is typically reflected in the degree to which the IS is considered to be supporting various functional areas within a firm, such as financial management, sales, marketing, etc.	BI system is supporting the financial management function in my organisation.	8	Adoption of BI systems was measured as BI support for eight functional areas in the organisation (Liang et al., 2007; Cooper and Zmud, 1990).
****Non-financial performance**	The extent to which the organisation improves efficiencies and effectiveness of customers, learning and development, and business processes.	Business process performance has been___.	14	Non-financial performance was measured using 14 prior items adapted (Elbashir et al., 2008). These items reflected the degree to which an organisation believes it has achieved its objectives with respect to improvement in business processes, customers and learning and development.
****Financial performance**	The extent to which the organisation has succeeded financially.	The increase in operating income is___.	6	Financial performance was measured using six prior items adapted from (Kallunki et al., 2011; Elbashir et al., 2008). These items reflected the degree in

Variable	**Conceptual Definition**	**Example Questionnaire Item***	**Number of items**	**Literature Source(s)**
				which an organisation believes it has achieved its objectives with respect to improvement in profit, sales growth, return on investment and cost savings.
****Sophistication of formal controls**	The extent in which formal controls are used in the organisation.	Contribution of our strategic planning systems to organisational performance outcomes has performed relative to expectation	10	Sophistication of formal control is measured using 10 items (Granlund, 2011; Kallunki et al., 2011). These items measure the degree to which an organisation believes it has achieved their objectives with ten formal controls such as strategic planning, cost control, budgeting system, performance monitoring, etc.
***Sophistication of informal controls**	The extent in which informal controls are used in the organisation.	We are satisfied with how our employees are able to achieve consensus seeking without needing management intervention	9	Sophistication of informal control is measured using nine items (Chenhall, 2006; Chenhall, 2003; Smith, 2007). These items measure the degree to which an organisation is satisfied with nine informal controls such as employee participation in decision making, communication channels, adaptation, information sharing etc.
	* All items measured on a Likert scale from 1=Strongly Disagree to 7=Strongly Agree ** All items measured on a Likert scale from 1= Much worse than expected to 7= Much better than expected			

5.18 Pre- and Pilot Testing of the Questionnaire

In identifying and developing the measures, prior literature was used to ensure content validity. "Content validity refers to the extent in which the measure represents all aspects of the construct" (Vonglao, 2017). Ten individuals were used to review the instruments and confirm its adequacy as well as to provide input on the types of participants/key informants who would be appropriate to complete the questionnaire on behalf of their organisation. The recommendations from these experts were used to enhance the content validity of the instruments. The recommendation of the experts included the extension of sophistication of formal control instruments by adding the contribution made by internal auditing systems to organisational performance outcomes (SFC6). In addition, return on operating profit was re-worded to increase on return on investment (FP3).

Thereafter, "pilot-testing was conducted to ensure the face validity of the instruments by determining if the survey would be understandable for participants and whether there might have been any ambiguous or confusing measurement items". The pilot test also helped with ensuring that the survey items were appropriate in the BI systems usage context. The pilot test was carried out by a "convenience sample" of executives and CFOs drawn from 20 organisations. These individuals were drawn from the same population as the main study but were not the same individuals that reviewed the instruments initially. Their responses helped to determine the face validity of the measures and allowed for some initial screening of the descriptive statistics of each scale, e.g., variation in responses and overall reliability measures. The financial performance instruments had eight items to be measured, two items were dropped (FP4 and FP6), while sophistication of informal control had 10 items to be measured, one item was dropped (SIC5). These items were dropped because the item loading was less than 0.50.

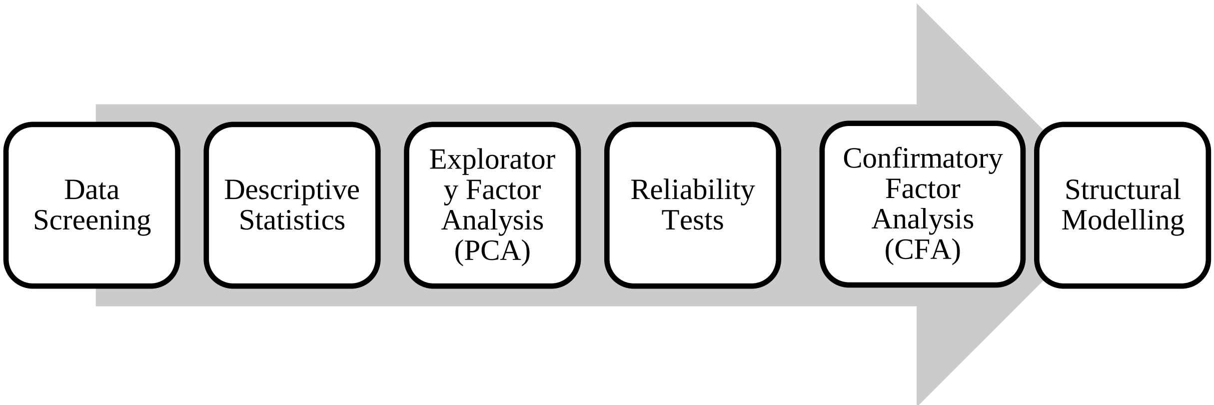
5.19 Final Instrument Administration

The final questionnaire for the organisational level study (refer Appendix D) was administered electronically to the sample described in section 5.5.2. The questionnaires were distributed through the emails directly to the respondents, in other case they were sent to the key contact person who then forwarded the instruments to the respondents with a cover letter/participant information sheet inviting them to participate, and if they chose to participate, they could click on a link to an online questionnaire. Reminder emails were sent after two weeks of sending the instruments to improve the response rate. All respondents were sent a reminder.

5.20 Data Analysis

Quantitative data analysis for each of the individual level study and the organisational level study proceeded using the tests described below and summarised in Figure 17. The data was analysed using statistical software SPSS AMOS version 25.

Figure 17 Steps Taken for Data Analysis



5.21 Data Screening

Although questionnaires circulated were pre-coded to eliminate the risk of coding error (Saunders et al., 2009), the data received from the respondents was screened to identify and eliminate errors before the data was further processed (Evans, 2010). Data coding is further described in the relevant chapters reporting on the results.

5.22 Descriptive Statistics

Descriptive statistics were used to describe the sample profile and the shape or distribution of the collected data.

Because the data of this study was collected using Likert scales, there was a question of whether the data analysis would be done using parametric or non-parametric tests. Gardner and Martin (2007) argued that the selection of the data analysis technique affects the conclusions drawn from the results. Nappo and Grassia (2008) contend that “Likert data is of an ordinal or ranked nature”, hence recommending the use of non-parametric techniques to yield valid results (Harpe, 2015). Importantly, Norman (2010) conducted a study using scale data and found that “parametric tests” such as “Covariance Based Structural Equation Modelling (CB-SEM)” and regression analysis can be used on data collected via Likert-type scales without fear of biased conclusions. The findings were consistence with those of Murray (2013) that parametric tests can be reliably conducted on “Likert scale data”.

Descriptive statistics reported include the means, standard deviations, skewness, and kurtosis of scale items. Frequency counts and percentages are also used in describing the sample profiles.

5.23 Exploratory Factor Analysis

Prior to tests of the hypotheses using path modelling techniques (discussed further below), it was first necessary to carry out an initial exploratory factor analysis (EFA) to uncover the underlining structure of the large set of variables (Vonglao, 2017; Abdi, 2010). The objective of this initial EFA was to establish the uni-dimensionality and underlying factor structure of the study's variables (Hair, Black, Babin and Anderson, 2010). EFA was carried out using "Principal Component Analysis (PCA)". The results obtained are presented in Chapter 6,7 and 8. The uni-dimensionality assessment must be made first before the validity and reliability could be tested. However, in the "uni-dimensionality step, the items with low factors loading (less than 0.6) should be deleted, while redundant items could either be deleted or constrained".

PCA allows for initial testing of convergent and discriminant validity. Items with lower loadings were deleted to confirm convergent and discriminant validity. Validity is concerned with whether the findings obtained through data collection provide a correct representation of the topic that is being investigated (Salkind, 2009). Validity of the instruments confirms as to whether the instruments being used are measuring what the researcher intend to measure and the accuracy of the concept being measured (Collis and Hussey, 2009). Furthermore, Collis and Hussey (2009) stated that a "valid instrument must cover the extent to which it provides adequate coverage of the topic under study" (Collis and Hussey, 2009).

Collis and Hussey (2009) summarised the three types of validity as follows:

- Content validity - this pertains to the scale measuring what it is supposed to measure and is established through the use of literature to guide the operationalization of variables, and the use of a pre-test involving academic and BI system experts (Collis and Hussey, 2009);
- Face validity -this pertains to the extent in which the scale is subjectively viewed as covering the concept it purports to measure and is established through the pilot study to identify low variation in responses and confusing items (Collis and Hussey, 2009);
- Construct validity including both "convergent validity and discriminant validity" - this pertains to the degree in which the test claim to be measuring and was established initial

using EFA as discussed above. EFA was carried out to uncover the underlining structure of the large set of variables. The objective of this initial EFA was to establish the uni-dimensionality and underlying factor structure of the study's variables (Hair et al., 2010). EFA checks if items load onto their expected constructs (convergent validity) and do not load onto factors (variables) they are not intended to measure (discriminant validity) (Fornell and Larcker, 1981).

5.24 Reliability Tests

Reliability pertains to whether the data is free of measurement error and results are reputable (Collis and Hussey, 2009). The "reliable instrument" reduces "errors and bias when analysing findings (Petty et al., 2012), offering consistent measurement across time and across the various items on an instrument" (Maxwell, 2005). A common approach in surveys when establishing reliability is internal consistency measure. The study also adopts "internal consistency" as a measure of "reliability" and which was confirmed using "Cronbach's alpha", and the generally accepted cut-off of 0.7 (Hair et al., 2010). Values less than that raises concerns regarding the presence of too much measurement error. The item to total correlations has also been reviewed from the internal consistency tests and items with low (0.30) item to total "correlations" would be dropped. The items with lower correlations were dropped.

5.25 Confirmatory Factor Analysis and Structural Equation Modelling

"Structural Equation Modelling (SEM)" analysis using AMOS was then performed. SEM provides for both a confirmatory test of the measurement model (relationship between each latent construct and its indicators) and a test of the structural model ("relationships between the latent constructs themselves") (Hair et al., 2010).

5.25.1 Confirmatory Factor Analysis

The "measurement models were tested using Confirmatory Factor Analysis (CFA)" (Hair et al., 2010). CFA tests if the measures selected are consistent with the proposed models or theories (Lee and Lings, 2008). The main function of CFA is to confirm if the variables selected measure the hypothesised model. The assessment of the measurement models through CFA procedure allows for final confirmation of uni-dimensionality, "validity and reliability" of items measuring the constructs. The factor structure results provide simultaneous assessment of item inter-correlations within the framework of "hypothesised relationships" between the "independent and dependent variables" (Lucadamo and Amenta, 2014; Russolillo, 2012).

After testing for “validity and reliability”, the items dropped during tests of the measurement model were not then carried through into the tests of the structural model (Hair et al., 2010).

5.25.2 Structural Model

This research aimed to establish the strength of the hypothesized path relationships between study variables by using covariance-based SEM (CB-SEM). Studies such as those of Kallunki et al. (2013); Chong and Eggleton (2003); Poorundersing (2008); and Tsui (2001) that have had an influence on the conceptualisation of this study’s research models have all relied on the use of Likert-scale data and subjected them to statistical tests using SEM. Consequently, this study used SEM statistical techniques. SEM has become a popular statistical technique widely used to test theory in various fields (i.e., information system, management science). SEM is a multivariate statistical procedure that consolidates both “multiple regression analysis and factor analysis” in testing the hypothesised model, to establish causality within latent (or construct) and observed variables that form part of the model (Barrett, 2007; Sangthong, 2020). “The ability of SEM to differentiate between direct and indirect relationships between variables and analyse the relationships between latent variables without random errors differentiates SEM from other simpler, relational modelling such as multiple regression analysis” (Fan and Sivo, 2005; Russolillo, 2012).

SEM allows the testing of all the hypothesized relationships in a research model (Figure 18 and Figure 20) at once (Hair, Ringle and Sarstedt, 2011). If the model fits the data, then the hypotheses will not be rejected as the model and the observed covariance matrices are equal (Awang, Afthanorhan and Mamat, 2016). This is important in statistics as one is trying to support the findings and hypotheses. SEM is concern with finding that the hypothesized model does not contradict the observed (real-world) data (Sangthong, 2020). Hoe (2008) suggests that a “conceptual difference of SEM from regression analysis is that in a regression model, the independent variables are themselves correlated (multi-collinearity)” which “influences the size of the coefficients found”. SEM allows the interactions amongst these variables to be modelled (Cheung and Rensvold, 2002). The model has a structural model indicating possible causal dependencies between endogenous and exogenous variables, and the *measurement model* displays the relations between “latent variables and their indicators” (Tarka, 2018). SEM allows the pathway to be specified in which hypothesized causal relationships between variables on the models are tested. The researcher examined the significance of the path coefficients as a basis from which to support/reject the hypotheses (Mohamad, Bin and Afthanorhan, 2014; Vonglao, 2017).

5.25.3 Parameter Estimation

Maximum Likelihood Estimation (MLE) is the method that can be used to estimate the "parameters of the model given the observations, by obtaining the parameter values that maximize the likelihood of making the observations, given the parameters" (Myung, 2003). MLE can achieve this by considering "the mean and variance as parameters and finding particular parametric values that make the observed results the most probable, given the model". In this study, MLE was used. The MLE was used because of its robustness even in the absence of multivariate normality assumptions. The MLE also makes it possible for the calculation of the chi-square as the most common measure of fit (Fan and Sivo, 2005).

5.25.4 Model Fit

SEM requires that model fit must be examined of an estimated model to determine how well it models the data. The fit statistics such as "Chi-square (X^2)", "Root Mean Square of Error Approximation (RMSEA)", "Goodness of Fit Index (GFI)", "Adjusted Goodness of Fit Index (AGFI)", "Comparative Fit Index (CFI)", "Tucker-Lewis Index (TLI)", "Normed Fit Index (NFI)", and "Chi-square degree of freedom" were examined to confirm the factor structure and indicated if the models and theories were acceptable or not (Barrett, 2007; Fan and Sivo, 2005). Table 10 describes different model fit criteria and acceptable levels.

Table 10 Model Fit Criteria and Acceptable Fit Level

Model Fit Criteria	Description	Acceptable level	Source
"Goodness-of-fit (GFI)"	"The GFI is the degree of fit between the hypothesized model and the observed covariance matrix".	0 (no fit) to 1 (perfect fit)	(Barrett, 2007)
"Normed fit index (NFI)"	"The NFI evaluates the discrepancy between the chi-squared value of the hypothesised model and the chi-squared value of the null model".	Value must exceed 0.9	(Fan and Sivo, 2005) (Byrne, 2013)
"Comparative fit index (CFI)"	"The CFI assumes that all latent variables are uncorrelated and compares the sample covariance matrix with the null model".	Value must exceed 0.9	(Fan and Sivo, 2005)

Model Fit Criteria	Description	Acceptable level	Source
“Incremental fit index (IFI)”	“The IFI’s purpose is to correct the issue of parsimony and sample size related to NFI”.	Value must exceed 0.9	(Byrne, 2013) (Hoe, 2008).
“Root mean square error of approximation (RMSEA)”	“Informs how well the model, with indefinite but optimally selected parameter estimates, would fit the population’s covariance matrix”.	Value must be <0.05	(Cheung and Rensvold, 2002)
“Chi-square ($\chi 2$ /DF)”	“To assess the magnitude of discrepancy between the sample and fitted covariance matrices”. The estimation process is dependent on the sample data	Value must be below 3	(Cheung and Rensvold, 2002)
“Tucker-Lewis Index **(TLI)**”	“The TLC utilises simpler models and is known to address the issue of sample size associated with NFI”.	Value must exceed 0.9	(Hoe, 2008).
“Relative Fit Index **(RFI)**”	“The RFI compares the chi-square for the hypothesised model to one from a “null”, or “baseline” model”.	Value must exceed 0.9	(Byrne, 2013)

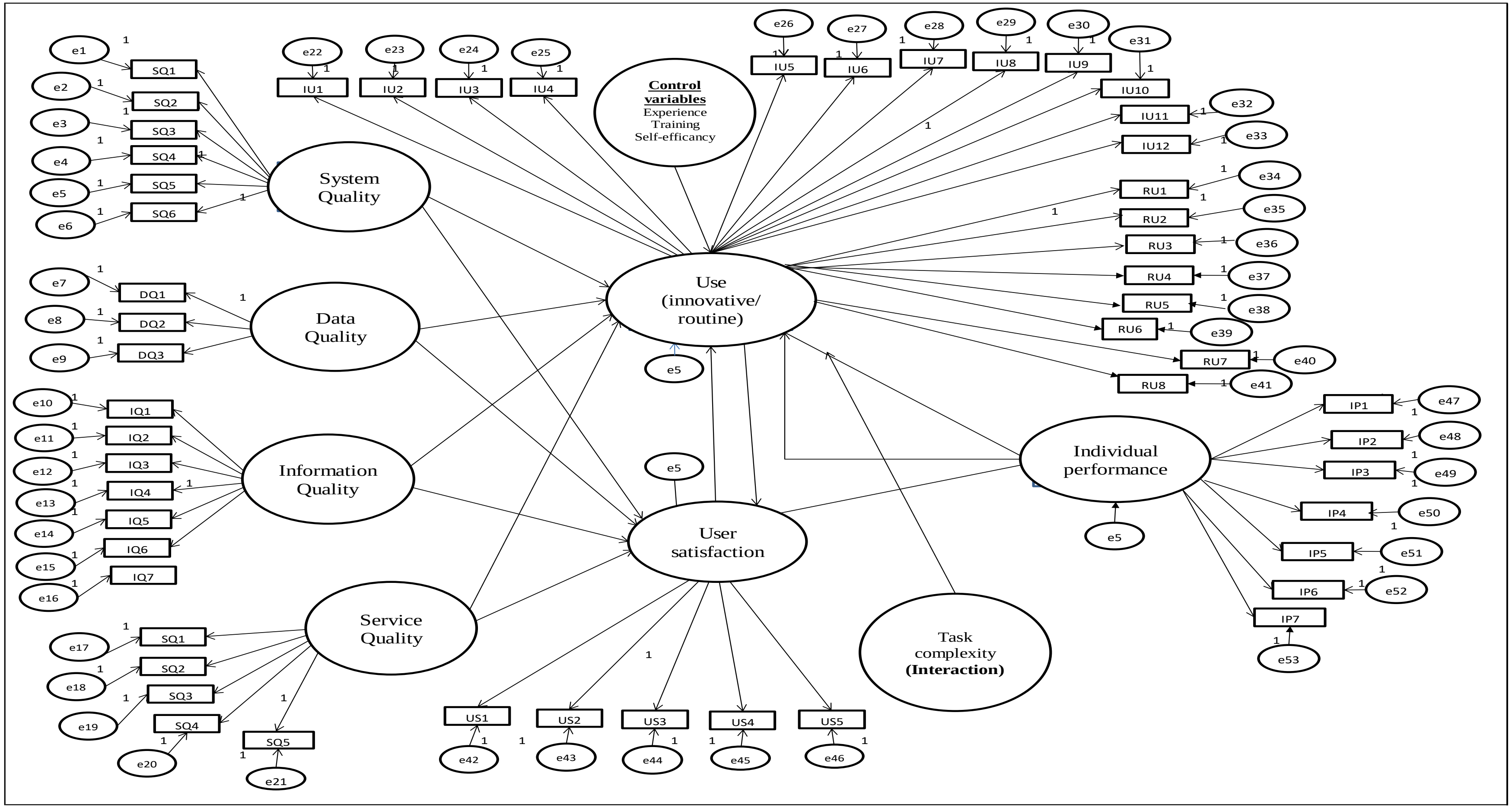
All of this study’s proposed models (i.e., individual and organisational model) were tested in the manner described above. For each model test, SEM goodness-of-fit indices were used to determine whether the pattern of variances and covariances in the data is consistent with each hypothesized theoretical model (Awang, Afthanorhan and Asri, 2015). The root mean square error of approximation (RMSEA) was used to evaluate the covariance structure of the model. “It reduces problems and inconsistencies commonly found in testing models with large sample sizes and has therefore become a helpful tool for guiding complex judgements about model utility”, “rather than functioning as a replacement for such judgements” (Hoe, 2008). For a good model fit, RMSEA should be less than or equal to 0.5. $\chi 2$ and other goodness of fit indices are also to be reported and compared to recommended acceptable values.

5.26 Measurement and Structural Models in the Individual-Level Study

As explained earlier, the first model tested was a cross-sectional test of the full model carried out using the data collected in wave 1.

There are thirteen hypotheses to be tested in addressing RQ1 and RQ2 as depicted in Figure 6.2. The SEM model tested addressed RQ1 and RQ2 as illustrated in Figure 18. The SEM model shows the relationships between the observed and latent variable in testing the hypothesis. In addressing RQ1, the first part of the model indicates four factors (system, data, information, and service quality) influencing the use (innovative and routine use) of the BI system. The four constructs were measured using 21 observed variable items. These four constructs in the path diagram are considered exogenous. RQ2 was addressed through measuring the causal relationship between use (innovative and routine), user satisfaction and individual performance considering the complex work of individual management accountants and other control variables i.e., experience and training. There were 32 observed variable items used to address use, user satisfaction and individual performance.

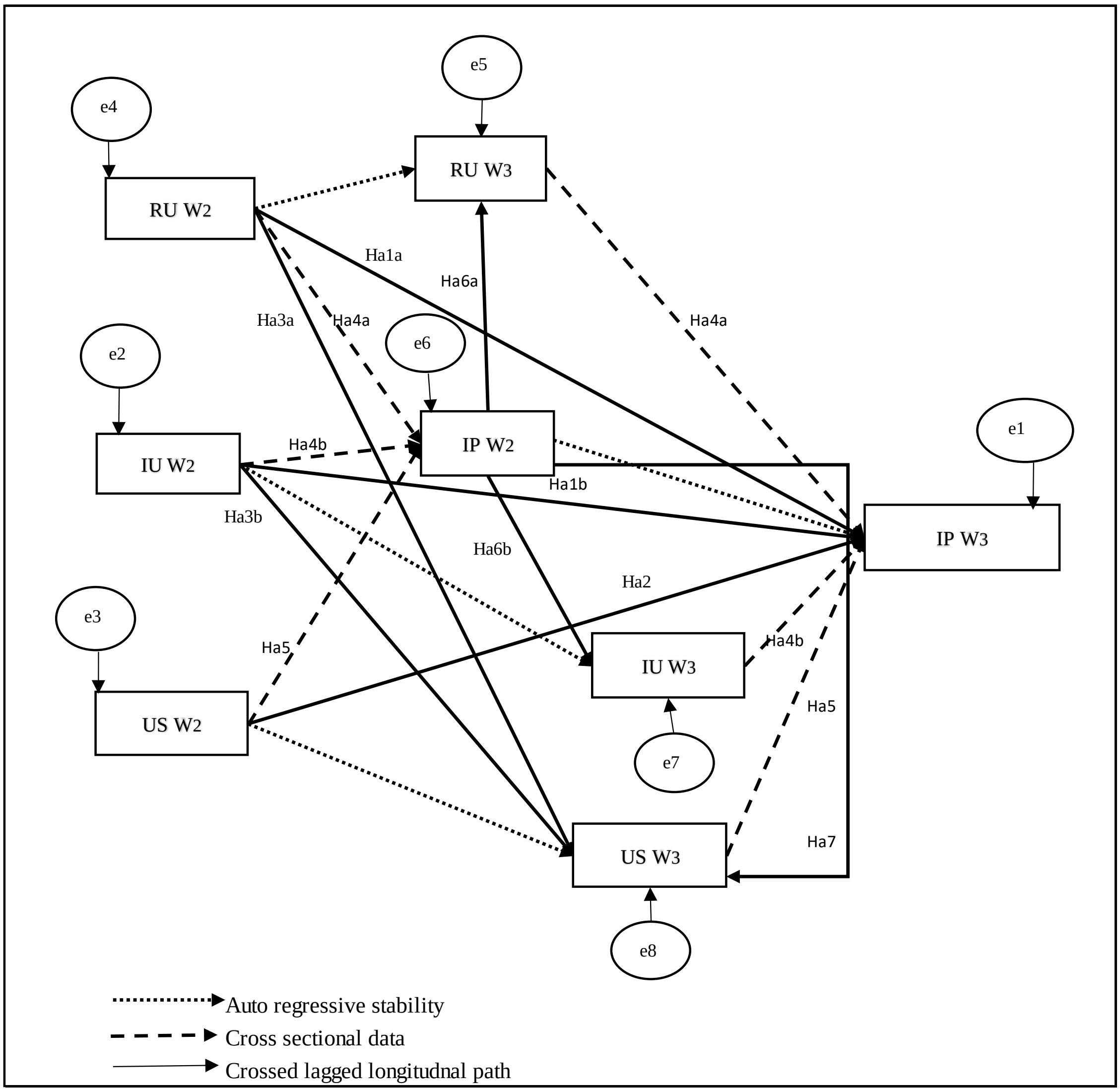
Figure 18 Structural Equation Model Tested in the Individual level



Following testing of the above model, a second longitudinal model was tested. First, paired-sample t-tests was used to compare scores on innovative, routine use; user satisfaction and performance in the various waves (i.e., W_1 versus W_2, and W_2 versus W_3).

Thereafter, the longitudinal model was tested by comparing various waves (i.e. W_1. versus W_2). The example of the longitudinal model tested is depicted in Figure 19. This examines the change in innovative use over the periods and assesses the impact of innovative use on user satisfaction.

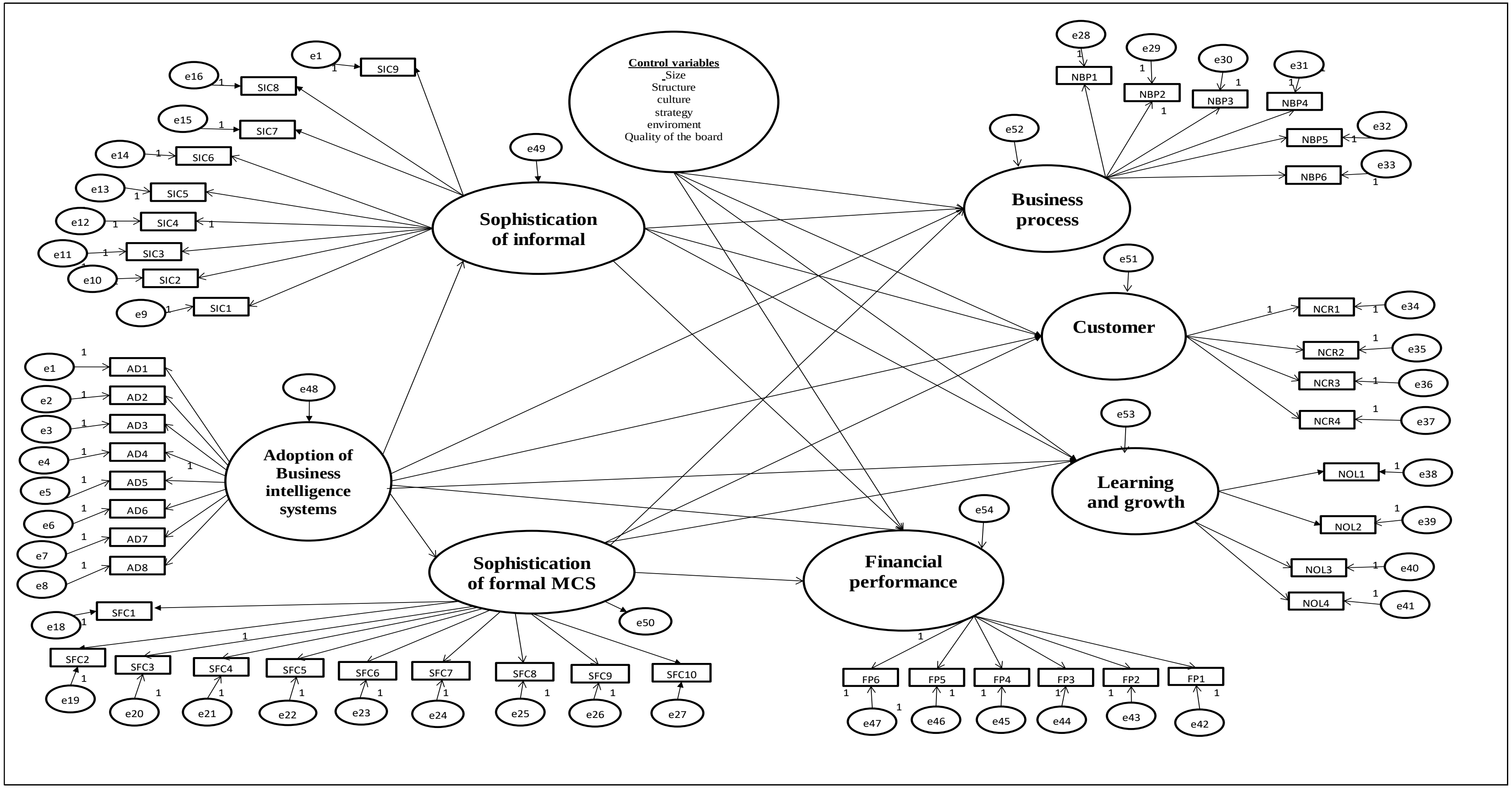
Figure 19 Example of Longitudinal Model Tested Using Data at Different Waves



5.27 Measurement and Structural Models in the Organisational-Level Study

In addressing RQ3, the quantitative data collected on the research model's variables was also analysed using SEM. There were nine (9) hypotheses to be tested in addressing RQ3 as depicted in Figure 13. The SEM model tested in addressing RQ3 is illustrated in Figure 20. The SEM model indicates the relationships between the observed and latent variable in testing the hypothesis. In addressing RQ3, the model indicates three constructs (Adoption of BI system, sophistication of MCS formal and informal) impacting on organisational non-financial performance and financial performance, taking into account the role of contingency factors. The three constructs were measured using 27 observed variable items, while non-financial performance was measured through six observed variable items and financial performance through 10 observed variable items.

Figure 20 Example Structural Equation Model Tested at an Organisational Level



5.28 Limitation and Threats to Validity

Internal validity is defined as the extent in which the gathered evidence of the study establishes a trustworthy cause and effect relationship amongst a treatment and outcome (Lee and Lings, 2008). This makes it possible for elimination of alternative explanations for a finding (Byrne, 2013). External validity refers to the way the outcome of the study can be applied in different settings. This explains the generalisations of the findings (Byrne, 2013). The study has several limitations and threats to internal and external validity which must be acknowledged. Firstly, data at the organisational level is to be collected using cross-sectional surveys, which introduces significant limitations in the ability to establish temporal precedence in the data and to make causal inferences (Collis and Hussey, 2009). For example, in answering RQ3 regarding the effects of BI system on organisational performance and MCS, the common method bias may exist as respondent responses represent behaviour at a single point in time. Secondly, common method bias might arise as data on all variables to be measured is collected from a single respondent (Lee and Lings, 2008). Causal inferences can thus be made only with reference to the theoretical reasoning presented in the literature and model development chapters.

In the study of individuals, data is collected over three waves (period). This strengthens internal validity and reduces threats to causal inference. Moreover, by collecting repeated measures at the different waves, the autocorrelation can be controlled, and cross-lagged effects estimated to strengthen causal inference. Thirdly, as with all survey studies, limitations arise with respect to response biases such as social desirability bias, as well as self-selection bias, amongst others (Lee and Lings, 2008; Byrne, 2013). This is suspected when there is high level of non-response. Fourthly, due to time constraints, some respondents may have been unavailable at that particular time. Fifthly, surveys measure the perception of the behaviour of the respondents not the actual behaviour. And finally, the response bias is also a threat to external validity where the people/organisations who respond are systematically different from those who did not respond. This constitutes a threat to the external validity of the findings as results are less generalizable (Byrne, 2013).

5.29 Conclusions

This chapter presented the research methodology followed in the study. The research method used is quantitative for both individual and organisational studies of the BI system. The individual study collected data over the three waves which was used to test the use and impact of BI systems on individual management accountants, with the data collected from wave 1 used on cross-sectional study, which tested the complete model. A longitudinal approach was also used to study the three waves. The organisational data was collected once, and the cross-sectional data was used to test the organisational model. The models were tested using SEM. The next chapter, Chapter 6, present the results of the data analysed to test the individual model.

CHAPTER 6: THE INDIVIDUAL USE AND IMPACT OF BUSINESS INTELLIGENCE SYSTEM

6.1 Empirical Results

In Chapter 5, the research methodology was developed. This Chapter analyses data collected from the empirical study. The RQ1 and RO1 "*To identify and empirically examine factors explaining observed variation in the innovative use of BI systems by individual management accountants*" is investigated and empirically tested. In addition, the RQ2 and RO2 "*To examine the impact of innovative use of BI systems on the individual-level performance of management accountants*" is investigated and empirically tested. A survey was conducted by means of distributing questionnaires to obtain opinions from individual management accountants in South African. The data collected from individual management accountants was used to test the hypothesised model of the individual BI system success. The initial sections discussed the sample size, demographics of the respondents, data screening and sample outliers. In addition, the next sections present descriptive statistics, assessment of normality and sample adequacy of the empirical data analysed. Furthermore, the principal component analysis, reliability and validity, correlation matrix are performed before the results of the model are analysed. Finally, the results of the model, discussion and conclusion are presented.

6.1.1 Sample Size

An invitation was sent to 1000 individual Management Accountants to participate in the study (refer Section 5.6 of Chapter 5). A total of 365 (a response rate = 36.5%) individual Management Accountants participated in the study. This relatively high response rate helps reduce threats to validity of conclusions arising from non-response bias[9]. Moreover, early (within first 5 days) and late respondents (in the last 5 days) were compared using t-tests and no differences in responses were observed, thus also suggesting non-response bias is of limited concern (Annexure G). However, two responses were eliminated as they were missing many data items. The final useable sample thus consisted of 363 "observations with sufficient data for meaningful statistical analysis", resulting in a response rate of 36.3%.

[9] For purposes of testing non-response bias, the strategy of comparing early and late respondents (as proxies for non-respondents) was employed (Annexure G).

6.1.2 Demographics

Before testing the SEM model using the collected data, “descriptive statistics” are presented to provide an overview of the sample under study. The “demographic profile of the respondents is presented” in Table 11. All 363 useable respondents provided their demographic information.

The results in Table 11 indicate that respondents who are aged between 36 and 40 years old (20.7%) were the highest category of age group, and 43.8% of the respondents were female. The results also indicate the following maximum percentages: 22% have 11-15 years’ experience in management accounting, 29,8% have 6-10 years of experience in their current organisations, 25.6% 6-10 years business intelligence system experience. Most respondents currently work on SAP business object (35%), 32.8% have more than 10 years of business intelligence experience at their organisation. Results further indicate that most of the employees have not attended formal training (56.7%), their sector of work is diverse and a slightly higher percentage work in finance (14%). In addition, 41.6% of the respondents hold a senior management position. Most of the respondents have a professional affiliation with the Chartered Institute of Management Accountants (CIMA) (55.1%).

Table 11 Demographics

Demographics	Category	Frequency	Percentage
Age	18-24 years	18	5.0
	25-29 years	32	8.8
	30-35 years	72	19.8
	36-40 years	75	20.7
	41-45 years	66	18.2
	46-50 years	48	13.2
	51-55 years	39	10.7
	> 55 years	13	3.6
Gender	Male	139	38.3
	Female	159	43.8
	Prefer not to say	65	17.9
Total experience in management accounting	<2 years	30	8.3
	2-5 years	43	11.8
	6-10 years	60	16.5
	11-15 years	80	22.0
	16-20 years	75	20.7
	>21 years	43	11.8
	Prefer not to say	32	8.8
	<2 years	15	4.1

Demographics	Category	Frequency	Percentage
Experience in management accounting at the current company	2-5 years	49	13.5
	6-10 years	108	29.8
	11-15 years	86	23.7
	16-20 years	88	24.2
	>21 years	17	4.7
Total experience in using the BI systems	<2 years	44	12.1
	2-5 years	60	16.5
	6-10 years	93	25.6
	11-15 years	91	25.1
	16-20 years	33	9.1
	>21 years	25	6.9
	Prefer not to say	17	4.7
Current BI system being used by your organisation	SAP business object	127	35.0
	SAS	32	8.8
	Oracle	37	10.2
	Microsoft Suite	57	15.7
	MicroStrategy	2	0.6
	IBM Cognos	3	0.8
	Qlikeview	13	3.6
	SAGE	35	9.6
	Sisense	5	1.4
	Sybase IQ	4	1.1
	ASYST	9	2.5
	Clear Analytics (Excel based)	39	10.7
Total years of experience with BI system at current organisation	None	1	0.3
	<1 year	65	17.9
	1-2 years	28	7.7
	3-5 years	51	14.0
	6-9 years	99	27.3
	>10 years	119	32.8
Training for this BI system attended	Yes	113	31.1
	No	206	56.7
	Prefer not to say	44	12.1
Sector of current employment as management accountant	Manufacturing	24	6.6
	Utilities and energy	44	12.1
	Logistics	22	6.1
	Retail	28	7.7
	Telecoms	32	8.8
	Airline	22	6,1
	Pharmaceutical	30	8.3
	Public sector	26	7.2
	Service	37	10.2
	Finance	51	14.0
	Mining	20	5.5
	Accounting	27	7.4
	Junior	19	5.2
	Entry management	35	9.6

Demographics	Category	Frequency	Percentage
Current management level	Middle Management	83	22.9
	Senior Manager	151	41.6
	Specialist	60	16.5
	Executive management	15	4.1
Professional qualification	CIMA	200	55.1
	SAICA	135	37.2
	Other	28	7.7

Overall, the demographic data suggests that respondents cover many organisations across various industries, they are representative of professionally registered Management Accountants, with sufficient years' experience at high managerial levels. The sample of Management Accountants also occupy high positions in their organisations. Although there were a somewhat larger proportion of female respondents than male respondents, the figures are somewhat in line with CIMA membership which is reported to be 49% female. Not all respondents were formally trained on BI and the usage experience varies from around one year to over 10 years. The sample is considered appropriate for testing the model of individual use and impacts of BI.

Therefore, data analysis could proceed to the next step.

6.1.3 Data Screening

Data collected were analysed using the "Statistical Package for the Social Sciences (SPSS) Version 25" screened for missing data. There were three responses with few data missing, the items affected were system quality, service quality and routine use (Table 12). The missing data were handled using the median of nearby points method. The median of the nearby points method is calculated using the average of the nearby surrounding values (Byrne, 2013). "These numbers are calculated using a span of nearby points option in SPSS program". The median is computed considering all values of the items construct data from the upper and lower, the calculated value is used to replace the missing value (Hair et al., 2010).

Table12 Responses with Missing Data

Item	Number of missing responses
System quality (SQ) Item 6	1
Service quality (SQa) item 3	1
Routine use (RU) item 8	1

6.1.4 Sample Outliers

Outliers are defined as data points that differ significantly from other observations (Hair et al., 2010). To identify potential outliers, any responses that are unusually high or unusually low values were screened (Tarka, 2018). Extreme responses might suggest that the respondents are not from the same population. The extreme values are typically a response more than three standard deviations above or below the sample mean (Hair et al., 2010). Standardised scores on an item reflect the number of standard deviations from the mean. The standardised scores of each respondent was examined on each questionnaire item and none were identified as outliers. This is not surprising given that the questionnaire items were all answered on a given scale.

6.1.5 Descriptive Statistics

The construct investigated in this study were measured using two different scales. Firstly, the constructs such as system quality, data quality, information quality, service quality, user satisfaction, individual performance, self-efficacy, and task complexity were measured on a seven-point Likert scale where the value of 1 corresponds to "Strongly disagree" and the value of 7 corresponds to "Strongly Agree". Secondly, the remaining constructs, such as routine use and innovative use were measured using a six-point Likert scale where the value of 1 corresponds to "Never" and the value of 6 corresponds to "Very often". The mid-point of the seven-point Likert scale is therefore "4". This means that when the mean values are below 4, most respondents tended to disagree with the statements. The values between 4 and 4.5 indicate that respondents tended to be more neutral. Where the means are above 4.5, most respondents tend to agree or strongly agree with the statements. The mean, standard deviation, skewness, and kurtosis of composites is presented in Table 13.

Table 13 Descriptive Statistics

Variables	Minimum	Maximum	Mean	Std. deviation	Skewness	Kurtosis
System Quality	1.83	6.67	5.3168	1.13940	-1.58858	1.75264
Data Quality	1.33	6.67	5.3994	1.12804	-1.38928	1.85944
Information Quality	1.71	6.57	5.0752	1.36415	-1.45001	0.68730
Service Quality	1.80	6.80	5.2920	1.12737	-1.70697	2.81466
User Satisfaction	1.00	6.60	3.3160	1.40999	0.97888	-0.47700

Variables	Minimum	Maximum	Mean	Std. deviation	Skewness	Kurtosis
Individual Performance	1.86	6.86	5.6482	0.97570	-2.41644	6.42743
System Efficacy	1.33	7.00	5.5197	1.27803	-1.50416	1.74016
Task complexity	1.00	7.00	5.0854	1.63565	-0.90636	-0.51636
Routine Use	1.63	5.88	4.1350	1.29352	- 0.49080	- 1.27255
Innovative use	2.00	5.92	5.0579	0.97870	- 1.75613	2.09226

* composite scores for each construct calculated as the arithmetic average of its original scale items weighted equally.

6.1.5.1 System quality (SQ)

System quality is constructed to extract information on individual management accountants' beliefs that the BI system is easy to use and availability to the users. The overall mean is 5.3 and standard deviation is 1.14 as presented in Table 13 above. This suggests that most respondents tend to agree that the BI system is useable and available. Six items were adopted from prior work related to attributes of IS use (Delone and McLean, 1992, 2003), and "measured using a 7-point Likert scale". As illustrated in Table 14, the mean of items ranges from 5.01 (1.230) and 5.48 (1.506). This suggest that respondents tend to agree with statements reflecting the quality of their BI systems.

Table 14 Statistical Results of SQ Items

Variable	Obs	Mean	Std. Dev.	Min	Max
SQ1	363	**5.48**	1.506	1	7
SQ2	363	**5.40**	1.278	1	7
SQ3	363	**5.28**	1.495	1	7
SQ4	363	**5.29**	1.328	1	7
SQ5	363	**5.43**	1.349	1	7
SQ6	363	**5.01**	1.230	1	7

6.1.5.2 Data quality (DQ)

Data quality is constructed to extract information on individual management accountants' beliefs that the BI system data inputs are accurate and complete. The overall mean is 5.4 and standard deviation is 1.13 as presented in Table 13 above. This suggests that most respondents tend to agree that the BI system data inputs are accurate and complete. Three items for data quality were adopted from prior work related to attributes of IS use (Hou, 2012; Wu, 2006), and “measured using a 7-point Likert scale”. As illustrated in Table 15, the mean of items ranges from 5.30 (1.294) and 5.51 (1.324). This suggests that respondents tend to agree with the data quality of their BI systems.

Table 15 Statistical Results of DQ Items

Variable	Obs	Mean	Std. Dev.	Min	Max
DQ1	363	**5.39**	1.294	1	7
DQ2	363	**5.51**	1.324	1	7
DQ3	363	**5.30**	1.298	1	7

6.1.5.3 Information quality (IQ)

The information quality construct is conceptualised to obtain information on individual management accountants’ beliefs that the information produced by the BI system is relevant, easy to use, accurate and complete. The overall mean is 5.1 and standard deviation is 1.34 as presented in Table 13 above. This suggests that most respondents tend to agree that the BI system information output is relevant, easy to use, accurate and complete. Seven items for information quality were adopted from prior work related to attributes of IS use (DeLone and McLean, 1992, 2003), and “measured using a 7-point Likert scale”. As illustrated in Table 16, the mean of items ranges from 4.87 (1.387) and 5.34 (1.748). This suggests that respondents tend to agree that their BI system outputs exhibit information quality.

Table 16 Statistical Results of IQ Items

Variable	Obs	Mean	Std. Dev.	Min	Max
IQ1	363	**5.01**	1.540	1	7
IQ2	363	**4.87**	1.644	1	7
IQ3	363	**5.02**	1.387	1	7
IQ4	363	**5.04**	1.748	1	7
IQ5	363	**5.17**	1.584	1	7
IQ6	363	**5.08**	1.515	1	7
IQ7	363	**5.34**	1.540	1	7

6.1.5.4 Service quality (SQa)

The service quality construct is conceptualised to obtain information on individual management accountants’ beliefs that the service quality received from the BI system support team is helpful, reasonable, on time and committed to resolving issues raised. The overall mean is 5.3 and standard deviation is 1.13, as presented in Table 13 above. This suggests that most respondents tend to agree that the BI system service quality received is helpful, reasonable, on time and committed to resolve issues raised. Five items were adopted from prior work related to attributes of IS use (DeLone and McLean, 1992, 2003), and “measured using a 7-point Likert scale”. As illustrated in Table 17, the mean of items ranges from 5.23 (1.236) and 5.42 (1.403). This suggest that respondents tend to agree that their BI systems are supported by relevant service quality indicators.

Table 17 Statistical Results of SQa Items

Variable	Obs	Mean	Std. Dev.	Min	Max
SQa1	363	**5.30**	1.319	1	7
SQa2	363	**5.42**	1.347	1	7
SQa3	363	**5.34**	1.236	1	7
SQa4	363	**5.23**	1.311	1	7
SQa5	363	**5.17**	1.403	1	7

6.1.5.5 User satisfaction (US)

The user satisfaction construct is conceptualised to obtain information on individual management accountants’ beliefs that, as users, they are satisfied overall with the use of the BI system. The overall mean is 3.3 and standard deviation is 1.41 as presented in Table 13 above. This suggests that most respondents tend to disagree that they are satisfied with the use of the BI system. Five items for user satisfaction were adopted from prior work related to user satisfaction with attributes of IS use (Popovič et al., 2012; Hajri et al., 2014), and “measured using a 7-point Likert scale”. As illustrated in Table 18, the mean of items ranges from 3.04 (1.514) and 3.49 (1.663). Thus, most respondents tend to report being somewhat less than satisfied with their BI systems.

Table 18 Statistical Results of US Items

Variable	Obs	Mean	Std. Dev.	Min	Max
US1	363	**3.49**	1.535	1	7
US2	363	**3.10**	1.663	1	7
US3	363	**3.46**	1.537	1	7
US4	363	**3.04**	1.613	1	7
US5	363	**3.49**	1.514	1	7

6.1.5.6 Individual performance (IP)

Individual performance is constructed to extract information on individual management accountants’ beliefs that the use of a BI system improves job performance, productivity and quality of decision making. The overall mean is 5.6 and standard deviation is 0.98, as presented in Table 13 above. This suggests that most respondents tend to strongly agree that the use of a BI system improves job performance, productivity and decision making. Seven items were adopted from prior work related to individual performance from IS use (Hou, 2012; Igbaria and Tan,1997) and were "measured using 7-point Likert scale". As illustrated in Table 19, the mean of items ranges from 5.56 (1.188) and 5.73 (1.302). This suggests that respondents tend to mostly agree that use of BI systems contributes to their individual performance.

Table 19 Statistical Results of IP Items

Variable	Obs	Mean	Std. Dev.	Min	Max
IP1	363	**5.69**	1.302	1	7
IP2	363	**5.58**	1.273	1	7
IP3	363	**5.66**	1.188	1	7
IP4	363	**5.56**	1.200	1	7
IP5	363	**5.73**	1.195	1	7
IP6	363	**5.64**	1.203	1	7
IP7	363	**5.66**	1.264	1	7

6.1.5.7 Self-efficacy (SE)

Self-efficacy is constructed to extract information on individual management accountants' beliefs that they have in themselves on innovative use of a BI system. The overall mean is 5.5 and standard deviation is 1.3, as presented in Table 13 above. This suggests that most respondents tend to mostly agree that they can use a BI system innovatively. The construct is used as a moderating effect on innovative and routine use of BI system. Three items were adopted from prior work related to IS use (Popovič et al., 2012; Hajri et al., 2014) and were "measured using 7-point Likert scale". As illustrated in Table 20 the mean of items ranges from 5.31 (1.464) and 5.82 (1.586). This suggests that respondents have relatively high levels of self-efficacy.

Table 20 Statistical Results of SE Items

Variable	Obs	Mean	Std. Dev.	Min	Max
SE1	363	**5.82**	1.464	1	7
SE2	363	**5.31**	1.586	1	7
SE3	363	**5.44**	1.551	1	7

6.1.5.8 Task complexity (TC)

Task complexity is constructed to extract information on individual management accountants' beliefs that the complexity of the task may result in innovative use of the BI system. The overall mean is 5.1 and standard deviation is 1.636, as presented in Table 13 above. This suggests that respondents tend to agree that they face relatively complex decision tasks, which may result in innovative use of the BI system. Eight items for task complexity were adopted from prior work related to individual IS use (Hou, 2012) and was "measured using a 7-point Likert scale". As illustrated in Table 21, the mean of items ranges from 5.02 (1.707) and 5.16 (1.872). This suggests that respondents tend to agree with statements on their task complexity.

Table 21 Statistical Results of TC Items

Variable	Obs	Mean	Std. Dev.	Min	Max
TC1	363	**5.03**	1.872	1	7
TC2	363	**5.15**	1.707	1	7
TC3	363	**5.08**	1.780	1	7
TC4	363	**5.02**	1.802	1	7
TC5	363	**5.16**	1.732	1	7
TC6	363	**5.11**	1.814	1	7
TC7	363	**5.05**	1.806	1	7
TC8	363	**5.09**	1.745	1	7

6.1.5.9 Routine use (RU)

Routine use is constructed to extract self-reports by individual management accountants on the frequency of their use of basic features of the BI system. The overall mean is 4.1 and standard deviation is 1.30, as presented in Table 13 above. This suggests that respondents tend to occasionally use basic features of the BI system. Eight items were adapted from prior work related to routine IS use (Popovič et al., 2012; Hajri et al., 2014) and "measured using a 6-point Likert scale". As illustrated in Table 22, the mean of items ranges from 3.96 (1.347) to 4.36 (1.691). This suggests that respondents tend to use routine features occasionally.

Table 22 Statistical Results of RU Items

Variable	Obs	Mean	Std. Dev.	Min	Max
RU1	363	**4.11**	1.472	1	6
RU2	363	**4.23**	1.347	1	6
RU3	363	**4.36**	1.477	1	6
RU4	363	**4.30**	1.534	1	6
RU5	363	**4.07**	1.498	1	6
RU6	363	**4.00**	1.507	1	6
RU7	363	**4.05**	1.612	1	6

Variable	Obs	Mean	Std. Dev.	Min	Max
RU8	363	**3.96**	1.691	1	6

6.1.5.10 Innovative use (IU)

Innovative use is constructed to extract self-reported data on how often individual management accountants use advanced features of the BI system. The overall mean is 5.1 and standard deviation is 1.02, as presented in Table 13 above. This suggests that most respondents report using more advanced features of the BI system often. Eight items were adopted from prior work related to attributes of IS use (Popovič et al., 2012; Hajri et al., 2014) and "measured using a 6-point Likert scale". As illustrated in Table 23, the mean of items ranges from 4.77 (0.975) to 5.34 (1.304). This suggests that respondents tend to be agree that they use more advanced features of the BI system often. Interestingly, the average on these usage items was higher than for routine use. While surprising, this is encouraging as it suggests management accountants are making more frequent use of advanced features, drilling down into data and constructing their own queries in response to their information needs. The implications for performance are examined in the sections that follows.

Table 23 Statistical Results of RU Items

Variable	Obs	Mean	Std. Dev.	Min	Max
IU1	363	**5.17**	0.975	1	6
IU2	363	**5.13**	1.215	1	6
IU3	363	**5.34**	1.050	1	6
IU4	363	**5.28**	1.274	1	6
IU5	363	**5.20**	1.177	1	6
IU6	363	**4.91**	1.254	1	6
IU7	363	**5.03**	1.084	1	6
IU8	363	**4.93**	1.296	1	6
IU9	363	**4.77**	1.069	1	6
IU10	363	**4.88**	1.304	1	6
IU11	363	**5.07**	1.114	1	6
IU12	363	**4.99**	1.268	1	6

6.1.6 Assessment of Normality

Table 13 above indicates "Skewness and Kurtosis coefficients" of all the constructs appearing in the model. The value for "skewness and kurtosis" between -2 and +2 is considered an acceptable indication of normality (George and Mallery, 2010). The results summarized in

Table 13 indicate an acceptable normality[10] given that the values of most kurtosis and skewness are between -2 and +2 except for individual performance which has a kurtosis of +6. However, the central limit theorem stipulates that deviation from the normality has little effect on the data for large sample size (above 300) (Muzaffar, 2016). This means that the abnormal kurtosis of the variables (items or constructs) exceeding the thresholds of -2 and + 2 will not be of concern in the overall results. Since the normality is not an issue, we can confidently use the principal component analysis to check if the items are loading with the latent constructs.

6.1.7 Sample Adequacy

Prior to proceeding with a "principal component analysis (PCA)" for the purposes of confirming the validity of the multi-item scales, it is necessary to first establish sample adequacy. The "adequacy of the sample is measured using the Kaiser-Meyer-Olkin (KMO)" test, as developed by Kaiser and Rice (1974). According to Field (2009), KMO measures sampling characteristic of the "ratio of the squared correlation between variables to the squared partial correlation between variables". The patterns of correlations vary between 0 to 1, if the value of the correlation is closer to 1, the correlations should produce reliable factors (Field, 2009). The values that are between 0.5 and 0.7 are poor, between 0.7 and 0.8 are good, valued between 0.8 and 0.9 are great, and above 0.9 are excellent (George and Mallery, 2010). The results of this study are illustrated below in Table 24, which indicates the KMO results as 0.896. The results of KMO indicates that the sampling adequacy falls withing the acceptable range. This indicate that the sampling size is adequate to yield the reliable factors.

Table 24 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.896
Approx. Chi-Square	20541,12
df	2016
Sig.	0.000

Bartlett (1954) developed a test that analysed whether the correlations between survey items is large enough for appropriate factor analysis. This test indicates the strength of the relationship within variables. The results of the research indicate that the Chi-square is 20541.12 and its

[10] Although survey data may sometimes be subject to polarised views, bimodal distributions, J curves and other anomalies, the data distributions were found acceptable.

significance is less than 0.001. This indicates that the data can usefully be analysed with the PCA analysis.

6.1.8 Principal Components Analysis (PCA)

Factor analysis (principal component) was conducted using the orthogonal rotation (Varimax) method. “This method was selected because it essentially captures the components with high eigenvalues and organises by order of importance” (Hair et al., 2011). Factor analysis functions on the assumption that measurable and observable variance can be reduced to a few latent variables that share common variance (Vonglao, 2017). This is known as the reduction of dimensionality. The unobserved factors are not measured directly but they are critical in an hypothetical model. The use of Exploratory Factor Analysis (EFA) is the first step in constructing scales (Hair et al., 2011). EFA is considered a useful first step prior to any Confirmatory Factor Analysis (CFA) at the early stages of developing the scale. EFA offers an opportunity to a researcher to explore the main dimension to produce a theory or model from latent constructs represented by sets of items (Sangthong, 2020). In this study, an exploratory analysis was considered necessary prior to formal model testing as there is not enough research evidence of the use and impacts of BI system on individual management accountants from the South African context and therefore, an initial exploratory approach was warranted.

Hair et al. (2010) stated that for a construct to be labelled a factor, it should have at least three variables (i.e., scale items), this can also depend on how the study has been designed. The number of factors produced depends on whether the variable might have a relationship with more than one factor (Murray, 2013). The use of a rotation matrix maximises high item loadings, while minimising low item loadings. This produces a more interpretable and simplified solution. The rotation on SPSS can be carried out using five various methods such as varimax, quartimax, equamax, direct oblimin and promax (Sangthong, 2020). This study chose to use varimax rotation to maximise high item loadings. Furthermore, a “factor score coefficient matrix was used in the scores menu and opted for listwise exclusion, sorting by size and suppression of absolute values less than 0.40 in the options menu”. The suppression of absolute values less than 0.40 allows for easier visual interpretation of the loadings. This study has 363 responses, and the factor loading was low at 0.50 or less. Items with loadings of less than 0.50 were eliminated from the study. Table 25 presents the results of factor analysis on the set of items. The principal component analysis indicate that 10 factors were extracted on 64 items. The total variance explained is 74%.

Table 25 Principal Component Analysis

"Rotated Component Matrix"										
"Component"										
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
SQ1							.751			
SQ2							.830			
SQ3							.821			
SQ4							.813			
SQ5							.863			
SQ6							.782			
DQ1										.837
DQ2										.845
DQ3										.847
IQ1				.878						
IQ2				.844						
IQ3				.850						
IQ4				.847						
IQ5				.891						
IQ6				.850						
IQ7				.839						
SQ1a								.838		
SQ2a								.856		
SQ3a								.869		
SQ4a								.798		
SQ5a								.848		
US1					.872					
US2					.898					
US3					.888					
US4					.900					
US5					.863					
IP1						.809				
IP2						.781				
IP3						.727				
IP4						.761				
IP5						.711				
IP6						.783				
IP7						.789				
SE1									.833	
SE2									.831	
SE3									.810	
TC1		.904								
TC2		.919								
TC3		.907								
TC4		.904								
TC5		.909								
TC6		.931								
TC7		.905								
TC8		.906								
RU1			.823							
RU2			.810							
RU3			.846							
RU4			.860							
RU5			.820							
RU6			.812							
RU7			.824							
RU8			.800							

"Rotated Component Matrix"										
"Component"										
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
IU1	.786									
IU2	.804									
IU3	.888									
IU4	.883									
IU5	.832									
IU6	.875									
IU7	.855									
IU8	.842									
IU9	.633									
IU10	.768									
IU11	.730									
IU12	.855									
Rotation Method: Varimax with Kaiser Normalization.										
Rotation converged.										
Total Variance Explained 74%										

The factor loadings in Table 25 are well above the threshold of 0.50. There are no items that were eliminated from the scale. All the factor loadings are high. The overall results of exploratory factor analysis indicate that all the items were associated with a component.

System quality (SQ) was measured through six items. As per Table 25, six items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, no items for service quality needed to be dropped.

Data quality (DQ) was measured through three items. As per Table 25, three items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, no items for data quality needed to be dropped.

Information quality (IQ) was measured through seven items. As per Table 25, seven items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, all items were retained.

Service quality (SQa) was measured through five items. As per Table 25, five items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, all items were retained.

User satisfaction (US) was measured through five items. As per Table 25, five items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, all items were retained.

Individual performance (IP) was measured through seven items. As per Table 25, seven items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, no items for individual performance needed to be dropped.

Self-efficacy (SE) was measured through three items. As per Table 25, three items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, no items for self-efficacy needed to be dropped.

Task complexity (TC) was measured through eight items. As per Table 25, eight items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, no items for task complexity needed to be dropped.

Routine use (RU) was measured through eight items. As per Table 25, eight items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, no items for routine use needed to be dropped.

Innovative use (IU) was measured through twelve items. As per Table 25, twelve items loaded highly onto the same factor and non-cross-loaded above 0.40 onto other factors. Therefore, no items for innovative use needed to be dropped.

Altogether, the model consisted of ten constructs which was confirmed by the underlying factor structure extracted by the PCA. The analysis could then proceed to examine the reliability of the scales.

6.1.9 Reliability and Validity

It is evident that for the scale to be valid and have practical usefulness, it must be reliable (Byrne, 2013). The reliability is the ability of the scale to produce the same results if it is used in the same conditions with the same objectives (Hair et al., 2010). In this study, the scale used 10 factors to measure the proposed research conceptual framework, namely system quality, data quality, information quality, service quality, routine use, innovative use, user satisfaction, individual performance, self-efficacy, and task complexity. Self-efficacy was used as an additional control variable in the model, while task complexity was considered for its direct and moderating effect on use and performance. Table 26 present the results of Cronbach's alpha, "Average Variance Extracted (AVE)" and "Composite Reliability (CR)". In measuring the reliability, the "Cronbach's alpha" was used. The scale is regarded as reliable if the "Cronbach's alpha" is at least 0.70 (Hair et al., 2010). Table 26 indicates that the "Cronbach's alpha" ranges from 0.779 to 0.973, this is above the recommended value of 0.70. The CR ranges from 0.83 to 0.96, which is above the threshold of 0.70. In addition, the AVE for each construct was calculated. The AVE has a minimum value of 0.57 which is more than the recommended 0.50 threshold.

Table 26 Results of Reliability and Validity

						Composite scores	
Variables	**Number of Initial items**	**Number of surviving items**	**Cronbach's alpha**	**"Average variance extracted (AVE)"**	**"Composite reliability (CR)"**	**Mean**	**Standard deviation**
System quality	6	6	0,912	0,643	0,915	5,3168	1,13940
Data quality	3	3	0,830	0,620	0,830	5,3994	1,12804
Service quality	5	5	0,905	0,659	0,906	5,0752	1,36415
Information quality	7	7	0,946	0,720	0,947	5,2920	1,12737
User satisfaction	5	5	0,939	0,754	0,939	3,2727	1,40999
Individual performance	7	7	0,901	0,566	0,901	5,6482	0,97570
Self-efficacy	3	3	0,779	0,763	0,906	5,5197	1,27803
Task complexity	8	8	0,973	0,685	0,945	5,0854	1,63565
Routine use	8	8	0,946	0,687	0,946	4,1350	1,29352
Innovative use	12	12	0,959	0,674	0,961	5,0579	0,97870

6.1.10 Correlation Matrix of Composite Scores

"Construct validity" can be achieved using "convergent and discriminant validity" (Sangthong, 2020). The inter-correlation has been calculated and presented in Table 27. The principle of discriminant validity requires that the measures of a construct should correlate more highly with each other and not correlate as highly with measures of other constructs (Hair et al., 2010). This principle can be tested by comparing inter-construct correlations with the AVE or square root of AVE of each construct. The "square roots of AVE" of each construct are presented along the diagonal of Table 27. These are shown as larger than the inter-construct correlations (Table 27). The "discriminant validity" is thus confirmed i.e., constructs share more variance with their own items than with other constructs in the model. Taken together, all these results then confirm the reliabilities, convergent and discriminant validities of the constructs. The model can then be tested in the next section.

Table 27 Results of Matrix of Composite Scores

	Mean (S.D.)	**SQ**	**DQ**	**IQ**	**SQa**	**US**	**IP**	**SI**	**TC**	**RU**	**IU**
SQ	5,32 (1,14)	**0,800**									

	Mean (S.D.)	**SQ**	**DQ**	**IQ**	**SQa**	**US**	**IP**	**SI**	**TC**	**RU**	**IU**
DQ	5,40 (1,13)	0,147**	**0,787**								
IQ	5,08 (1,36)	0,132*	0,111*	**0,848**							
SQa	5,29 (1,13)	0,150**	-0,022	0,044	**0,811**						
US	3,24 (1,42)	0,122**	0,138**	0,065	-0,085	**0,872**					
IP	5,65 (0,98)	0,277**	0,081	0,160**	0,084	0,155**	**0,750**				
SE	5,53 (1,26)	-0,016	-0,028	-0,095	0,034	-0,082	-0,003	**0,874**			
TC	5,09 (1,64)	0,165**	0,141**	-0,038	-0,001	0,119**	0,015	-0,017	**0,827**		
RU	4,14 (1,29)	0,234**	0,163**	0,255**	0,137**	0,068	0,271**	0,045	0,047	**0,829**	
IU	5,06 (0,98)	0,197**	0,147**	0,177**	0,139**	0,130**	0,279**	0,115*	0,138**	0,309**	**0,816**
**. "Correlation is significant at the 0.01 level (2-tailed)".											
*. "Correlation is significant at the 0.05 level (2-tailed)".											

6.2 Results of Model Testing

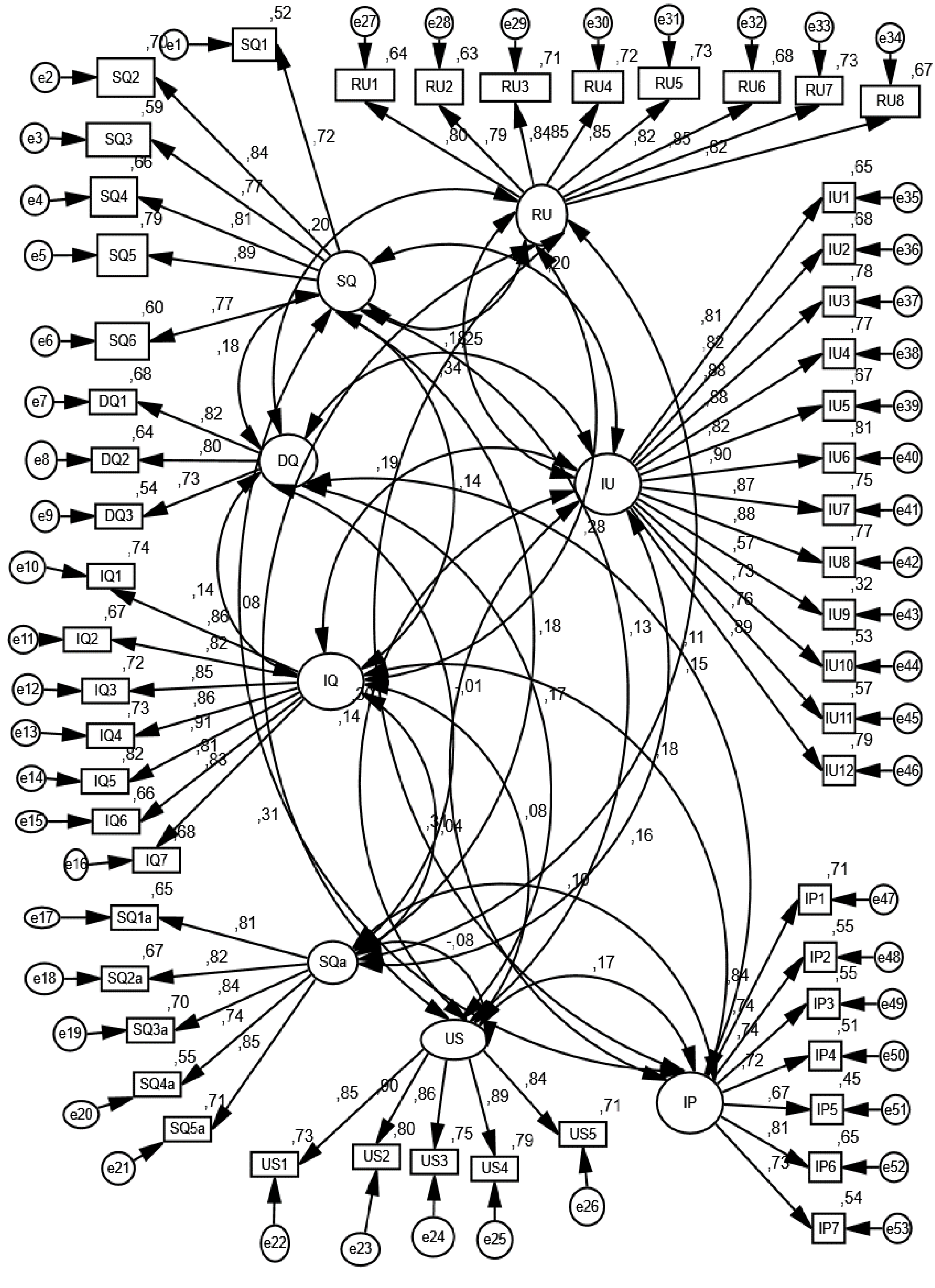
This section uses the data collected to formally test the study's measurement and "structural model" in detail. Before the hypothesised structural model can be tested, it is advisable to perform CFA as a final test of the "measurement model" to identify if all the items are loading properly on the hypothesised constructs in the model. The CFA was used to test the hypothesis with respect to sources of variability responsible for the commonality among a set of scores. The CFA analysis excluded two control variables with 11 measuring items (three for self-efficacy and eight for task complexity) and used only the 53 items measuring the main variables, none of which were dropped in the "exploratory factor analysis (PCA)" stage. The CFA was used to confirm that the proposed factor structure is a good fit to the data.

The second step was to use "Structural Equation Modelling (SEM)" to test the hypotheses represented by the relationship between independent and dependent variables, i.e., the structural model. The SEM model was conducted using AMOS version 25. AMOS is easier to use as the path diagrams are simplified compare to other software such as LISREL, STATA, etc. (Sangthong, 2020).

6.2.1 CFA Model Results

The CFA was used to assess the relationships between various constructs within the developed theoretical model and their measurement items. In assessing the model, it is important to look at the measurement model fit and measure the validity of the model being tested. In the process of evaluating the measurement model in the CFA, there is no need to differentiate between exogenous and endogenous constructs. Differentiating between exogenous and endogenous constructs is only necessary during the model testing. Figure 21 indicates all variables being linked together and the measured variables (construct items) are shown in rectangular shapes. The covariance is illustrated in Figure 21 by two headed arrows, the causal relationship is indicated by one-headed arrows. The model illustrated in Figure 21 includes only the main effects constructs and measurement items. Self-efficacy, experience, training, and task complexity were excluded. Therefore, the model in Figure 21 only focuses on system quality, data quality, information quality, service quality, user satisfaction, innovative use, routine use, and individual performance.

Figure 21 Initial CFA Measurement Model



6.2.2 Goodness of Fit Indices

The "maximum-likelihood" method was adopted to estimate the model's parameters and all analyses were conducted on covariance matrices. There are model fit indices that need to be considered when analysing the model goodness-of-fit. The first step is to assess the Chi-square (X^2) of the model being tested. The X^2 was found to be high and the ratio of X^2 / DF=12 is higher than the recommended three, which indicates that the data does not fit the model. This test may however reject the hypotheses unnecessarily (Hair et al., 2010) as even small differences between the observed model and the good model fit might be found to be significant. The fit indices were as follows (Table 28): [GFI= 0.790; NFI=0.854; CFI=0.924; IFI=0.925; RMSEA=0.050; DF=1297; TLI=0.919 and RFI=0.844]. The validity of the CFA model indicates that some model fit indices were not satisfactory. However, the main objective of the CFA model was to check if all the items of the scale are loading on the model. The CFA test was conducted to confirm construct validity and factor loadings (Serrano Archimi, Reynaud, Yasin and Bhatti, 2018). It was not meant to test the hypotheses among the constructs. The results indicate that all the items are loading appropriately and in line with theory. The factor loadings of this model range between 0.633 to 0.931, which is above the prescribed threshold of 0.50. The next section tested the hypothesised model.

Table 28 Goodness of Fit Indices

Fit Index	Recommended Value	CFA Results	Original Structural Model	Final Structural Model
Goodness-of-fit (GFI)	Less than 0.80 (No fit) Between [0.80-0.90] (acceptable) Above 0.90 (Perfect fit)	0.790	0.956	0.994
Normed fit index (NFI)	Less than .80 (poor) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.854	0.648	0.959
Comparative fit index (CFI)	Less than 0.90 (poor) Above 0.90 (good)	0.924	0.733	0.990
Incremental fit index (IFI)	Less than 0.90 (poor) Above 0.90 (good)	0.925	0.764	0.991
Root mean square error of approximation (RMSEA)	Less than 0.05 (good) Between [0.06-1] (acceptable) Above 1 (poor)	0.050	0.060	0.027
Chi-square ($\chi 2$ /DF)	Less than 3 (good) Between [3-5] (acceptable)	12	4	2

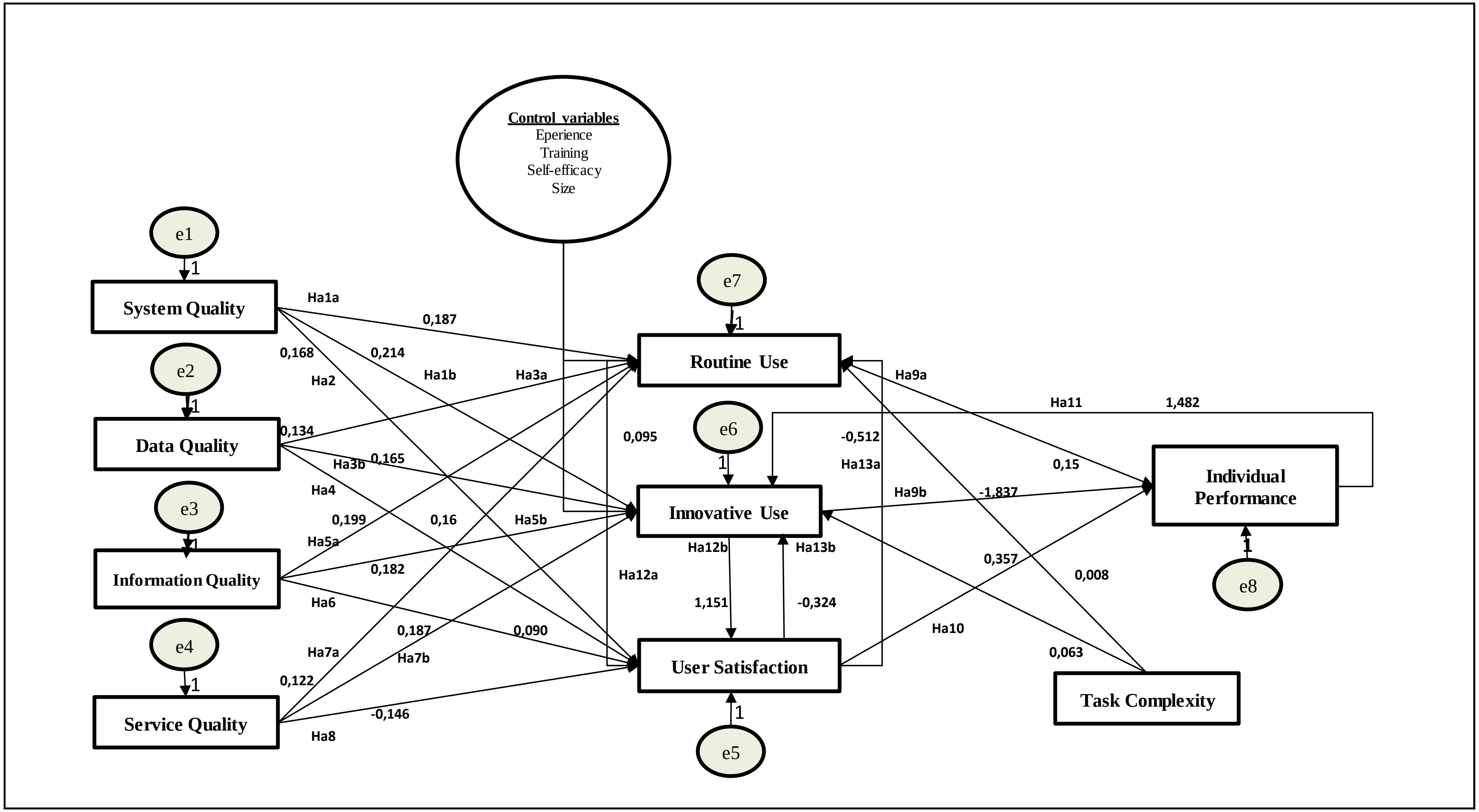
Fit Index	Recommended Value	CFA Results	Original Structural Model	Final Structural Model
	Above 5 (poor)			
Tucker-Lewis Index (TLI)	Less than 0.80 (bad) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.919	0.560	0.960
Relative Fit Index (RFI)	Less than 0.80 (poor) Between [.80-.90] (acceptable) Above .90 (good)	0.844	0.420	0.835

6.2.3 Original Structural Model testing

The above presented results indicate that reliability, convergent validity, and discriminant validity have been confirmed by both EFA and CFA techniques. The next stage was to test the hypothesised relationships between the exogenous and endogenous latent constructs (refer to Figure 6), which is done through the test of the structural model. In this stage, the relationships between independent and dependent variables are specified. The causal relationships between independent and dependent variable are indicated through a one head arrow. The covariance between independent variables is indicated by two header arrows. In this study, only "free" pathways are modelled for hypothesised causal relationships between the variables that are being tested. The free pathways are left free to vary, there are no fixed pathways as dictated by previous studies (Serrano Archimi et al., 2018; Hair et al., 2010; Sangthong, 2020) in this model.

The test of the originally hypothesised model is illustrated in Figure 22. Results indicate that there is a poor model fit. There is a need to improve the model fit to test the causal relationships amongst variables. The original model indicates the P=0.000 which is significant, however the X^2 / DF=4 which is higher than the recommended value of less than three. The fit indices as illustrated in Table 28 are as follows: [GFI=0.956; NFI=0.648; CFI=0.733; IFI=0.764; RMSEA=0.060; TLI=0.560; RFI=0.420] indicating a very bad fit of the model. There is a need for the model improvement so that a better model fit can be achieved. In improving the model, some of the constructs or hypotheses may have to be dropped and some of the variables may also have to be removed. In addition, some of the constructs may be constrained to zero, this means that they will not be part of the model that is being tested. The error estimate co-variance may also be drawn to improve the model fit.

Figure 22 Original Measurement Model Test Results



6.2.4 Final Model testing

The results of final SEM AMOS model are presented in Figure 23, innovative use of the BI system is modelled as a second order factor with the latent scores of first order (system quality, data quality, information quality and service quality) modelled as factors influencing the innovative use of the BI system. Innovative, routine and user satisfaction have an impact on individual performance of the management accountants. Although it was hypothesized in Chapter 3 (hypothesis 14) that task complexity would moderate the relationship between both routine, innovative use, and performance, it was decided to initially include task complexity within the research model as a direct determinant of routine and innovative use. Its moderating effect was tested subsequently (refer section 6.2.5 below). Self-efficacy is an additional determinant variable on innovative and routine use of BI system. *However, the final model only included the control variables paths where a preliminary run found a significant effect and left out the paths where there was no relationship.*

The final model indicates the P=0.263 which is not significant, compare to the default model, however the X^2 / DF=2 is acceptable as it is within the recommended value of less than three. Based on the second run of the model, the results of model fit have improved as presented above in Table 28. The fit indices are as follows: [GFI=0.994; NFI=0.959; CFI=0.990; IFI=0.991; RMSEA=0.027; DF=7; TLI=0.960; RFI=0.835] indicating a good model fit in most of the indices. The hypotheses not presented in Figure 23 (Ha11,12 and 13) were removed in order to improve the model fit; they are no longer part of the model as they were not significant. Those paths were compromising the model fit.

6.2.4.1 Model improvement steps taken

To improve the model, fit, the following improvements were undertaken. These improvements were identified by examining the AMOS output.

First, instead of modelling IP--->IU (Ha11), this was removed on the model as the standardised regression weight was greater than 1.0 as recommended by Hair et al. (2010). The standardised regression weight needs to fall between (1: -1). High correlation may affect the statistical power of the model and compromise the model fit (Hair et al., 2010). In this case, high correlation affected other critical paths to be insignificant and negative; this was a problem as it made the interpretation of the model a challenge.

Second, instead of modelling US ---> IU (Ha13a and Ha13b) path in this way, the hypothesis was dropped to improve the model fit. This path (Ha13) was insignificant with negative regression weight of -0,512 and -0,324 respectively (refer to Figure 22); this path was freed from the model to improve the model fit.

Thirdly, Self-efficacy was modelled only for its effects on routine and innovative use and not as a determinant variable. The re-modelling was done to improve the model fit. In addition, size, training, and experience were also removed to improve the model fit. They were not significant.

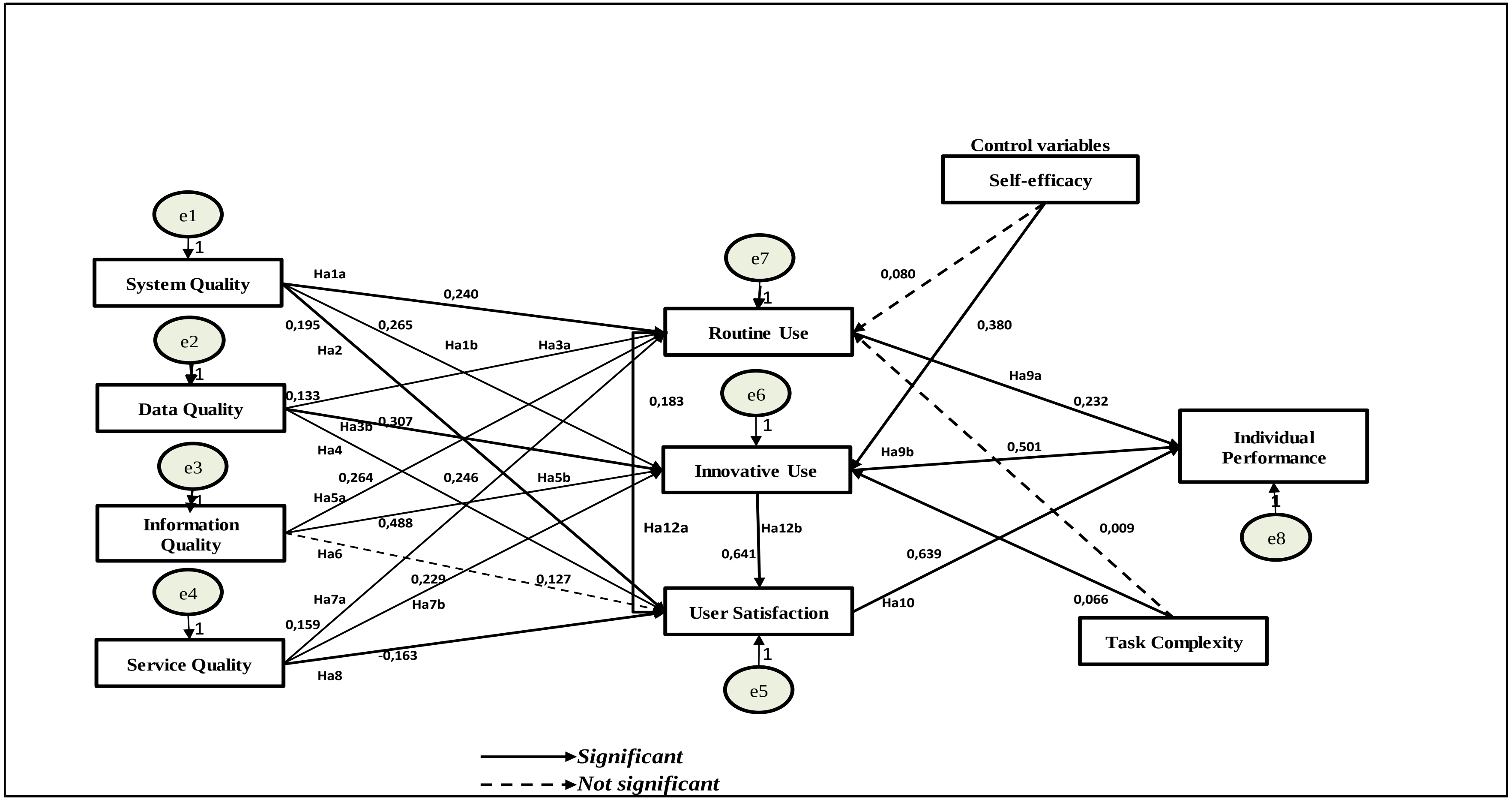
Finally, Table 29 indicates the modification indices with high covariance that may be covaried if they will not compromise the theoretical model being tested (Fan and Sivo, 2005). In improving the model fit, the below modification of indices were covaried.

Table 29 Modification Indices

Covariances	M.I.	Par Change
e2<-->e3	4,229	0,165
e1<-->e2	7,435	0,183
e3<-->e4	20,243	0,28

The results after this final improvement are shown next.

Figure 23 Final Measurement Model Test Results (covariance-arrows were removed to achieve better presentation of the model)



The significant paths are indicated in one header arrows, while the paths that are not significant are indicated by dotted one header arrows. The final indices suggest it was acceptable to proceed with an examination of the hypothesised relationships within the model. Table 30 indicates the path coefficients of the "hypothesised relationships within the proposed research model".

Table 30 The Results of Hypothesised Model

Hypothesis		**Estimate**	**S.E.**	**C.R.**	**P**	**Supported**
Ha1a	RU<---SQ	0,240	0,065	3,681	***	Yes
Ha1b	IU<---SQ	0,265	0,072	3,665	***	Yes
Ha2	US<---SQ	0,195	0,095	2,044	0,039	Yes
Ha3a	RU<---DQ	0,133	0,056	2,375	0,005	Yes
Ha3b	IU<---DQ	0,307	0,139	2,202	0,023	Yes
Ha4	US<---DQ	0,246	0,127	1,945	0,050	Yes
Ha5a	RU<---IQ	0,264	0,068	3,882	***	Yes
Ha5b	IU<---IQ	0,488	0,113	4,330	***	Yes
Ha6	US<---IQ	0,127	0,259	0,490	0,627	Not supported
Ha7a	RU<---SQa	0,159	0,078	2,041	0,040	Yes
Ha7b	IU<--- SQa	0,229	0,121	2,463	0,009	Yes
Ha8	US<--- SQa	-0,163	0,074	-2,215	0,027	Not supported (opposite sign)
Ha9a	IP<--- RU	0,232	0,069	3,362	***	Yes
Ha9b	IP<--- IU	0,501	0,178	2,815	***	Yes
Ha10	IP<--- US	0,639	0,192	3,328	***	Yes
Ha11	IU <-- IP					Dropped from model
Ha12a	US <-- RU	0,183	0,132	1,383	0,359	Not supported
Ha12b	US <-- IU	0,641	0,303	2,116	0,034	Yes
Ha13a	RU < -- US					Dropped from model
Ha13b	IU < -- US					Dropped from model
Determinant 1	RU<--- SE	0,08	0,148	0,525	0,600	Not supported
Determinant 2	IU<--- SE	0,38	0,182	2,087	0,037	Yes
Determinant 3	IU<--- TC	0,066	0,03	2,213	0,027	Yes
Determinant 4	RU<--- TC	0,009	0,039	0,227	0,821	Not supported
SQ=System quality DQ=Data quality IQ=Information quality SQa=Service quality US=User satisfaction RU=Routine use IU=Innovative use IP=Individual performance SE=Self-efficacy TC=Task complexity						

Table 31 R-squared Results

Variables	Estimate
US	0,274
IU	0,340
RU	0,199
IP	0,457

As presented in Table 30, nine out of eleven hypotheses were directly supported on the model being tested. The factors influencing the innovative use [SQ ($p<0.001$); DQ ($p<0.05$); IQ ($p<0.001$) and SQa ($p<0.01$)] of the BI system were found to have positive significance influence on the behaviour of the user to use the BI system innovatively. These support Ha1b, Ha3b, Ha5b and Ha7b. This means that improving system quality, data quality, information quality and service quality will encourage the management accountants to use more innovative features of the BI system. The factors influencing the innovative use of the BI system were also found to have positive significance influence on the behaviour of the user to use the BI system routinely [SQ ($p<0.001$); DQ ($p<0.01$); IQ ($p<0.001$) and SQa ($p<0.05$)]. These results support Ha1a, Ha3a, Ha5a and Ha7b. In addition, system quality ($p<0.05$) and data quality ($p<0.05$) were found to improve individual user satisfaction in support of Ha2 and Ha4. Service quality ($p<0.05$) was found to have an unexpected significant negative influence on user satisfaction, therefore Ha8 was rejected as the relationship was of the opposite direction. This means that the improvement in service quality reduces the user satisfaction. This could mean that users who often tend to rely on the team that is supporting the BI system would tend to be more dissatisfied with using the system themselves. Information quality does not have a significant effect on user satisfaction as its significance level ($p >0.05$) is greater than 0.05. These means improving Information quality will not translate into user satisfaction. Therefore, Ha6 is Rejected. This is surprising, given the purpose of BI systems and is discussed further below.

The innovative use of the BI system had a direct positive influence on the improvement of the individual performance of the management accountants. Hence, Ha9b ($p<0.001$) path is supported. The routine use of the BI system also has a direct positive influence on individual performance of the users. Hence Ha9a ($p<0.001$) path is supported. Both types of use are important as both have an independent direct positive influence on improvement of individual performance of the management accountants. User satisfaction has a significant effect on individual performance of management accountants of the BI system, hence Ha10 path ($p<0.001$) is supported. The users who are satisfied by using the BI system are likely to improve their individual performance at work. Innovative use of the BI system had a direct positive influence on user satisfaction, hence Ha12b ($p<0.05$) is supported. While routine use had no direct positive influence on user satisfaction, hence Ha12a ($p>0,05$) is rejected. The innovative use of BI system improves the user satisfaction of individual management accountants. Furthermore, it was also found that the model explained 27.4% of the user satisfaction variance (R^2), 34.0% of innovative use variance (R^2), 19.9% of routine use variance (R^2) and 45.7% individual performance variance (R^2).

Self-efficacy was introduced as an additional control variable in the model influencing routine and innovative use. Self-efficacy provides a judgement on whether an individual can reach their intended goals. The hypothesised model indicates that self-efficacy has a positive significant influence on innovative use of the BI system. However, there is no significant influence on routine use of the BI system. This confirms that individuals with high self-efficacy are likely to use the innovative features of the BI system and improve their individual performance, but routine use does not demand a high degree of self-efficacy.

6.2.5 Moderating Effects

As initially hypothesized, task complexity was considered a possible moderator of the relationship between use and performance. To examine this possible moderating effect, an additional model was tested to accommodate the task complexity as a moderator. For this purpose, interaction terms were calculated between task complexity and the two use constructs. As per recommendations, the variables were centred prior to analysis, which means that performance is a function of use (innovative and routine) plus task complexity and the interaction effect (innovative use x task complexity, and routine use x task complexity). Hair et al. (2010) stated that it is advisable to look at the model's goodness of fit, the significance of the path coefficients and the sign of the path when reaching conclusions about moderation.

The test of the hypothesised model is illustrated in Figure 24. Results indicate that there is a good model fit. There is no need to improve the model fit to test the moderating effects of task complexity on use and performance. The original model indicates the $P<0.001$ which is significant, however the X^2 / DF=1 is acceptable as it is within the recommended value of less than three. The fit indices are as follows: [GFI=0.915; NFI=0.899; CFI=0.946; IFI=0.946; RMSEA=0.067; DF=144; TLI=0.935; RFI=0.899] indicating most fit indices of the model are good. There is no need for the model improvement as most of the model fit indices were acceptable.

Figure 24 Results of Moderating Effect Model

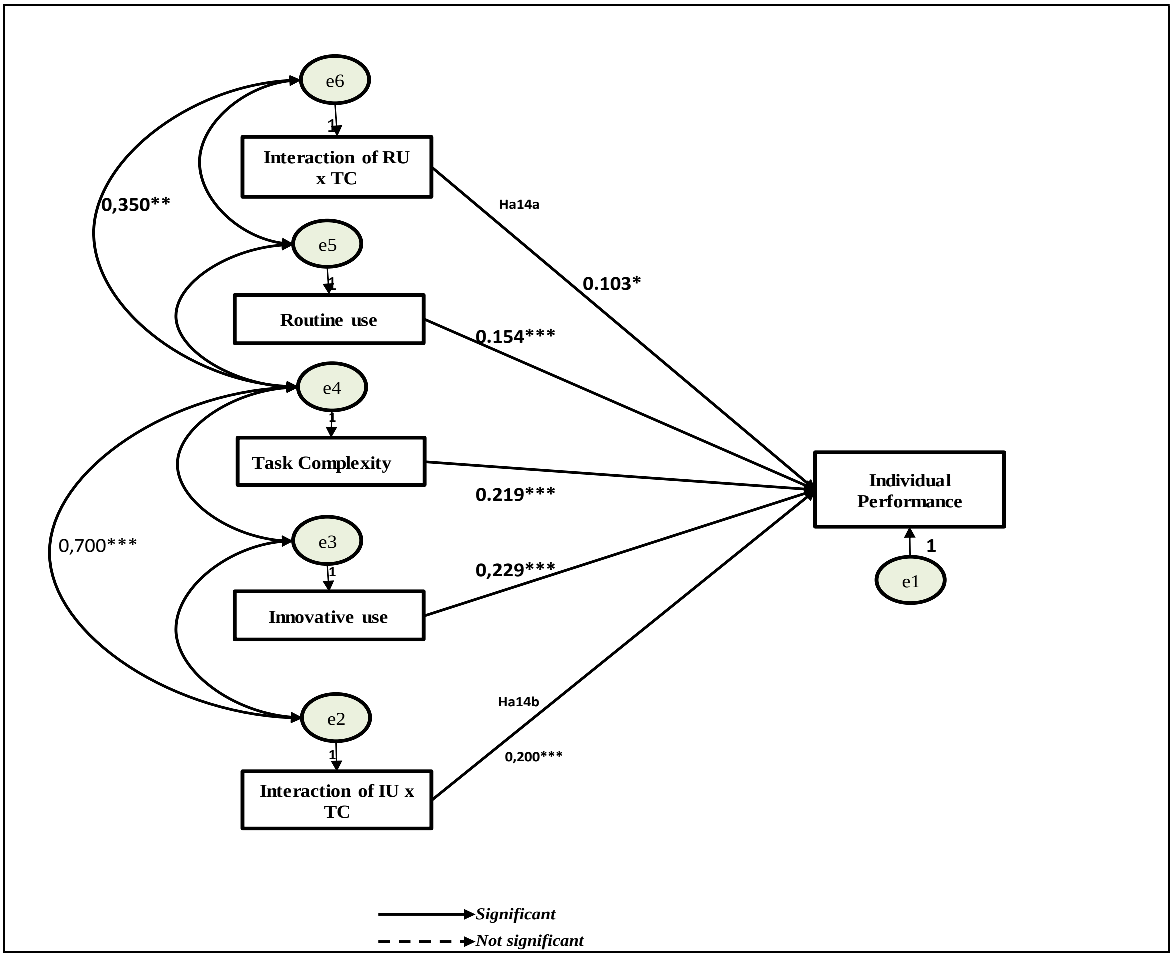


Table 32 The Results of Moderating Effects Model

Hypothesis		Estimate	S.E.	C.R.	P	Supported
Ha14a	IP<---IN_RU	0,103	0,050	2,032	0,042	Yes
Ha14b	IP<---IN_IU	0,200	0,047	4,255	***	Yes
	IP<---TC	0,219	0,056	3,921	***	Yes
	IP<---RU	0,154	0,043	3,538	***	Yes
	IP<---IU	0,229	0,056	4,069	***	Yes
IP=individual performance; TC=task complexity; RU=innovative use; IU=innovative use; IN_RU= interaction effect (routine use x task complexity); IN_IU= interaction effect (innovative use x task complexity)						

The above results indicate that the complexity of the management accountant's tasks increases their opportunity to use the BI system innovatively to support their management accounting function (p<0.001). Importantly, the task complexity has also a moderating effect on routine use and performance ($p<0.050$). Both types of use are moderated by task complexity significantly on individual performance, however task complexity moderate routine use less as compared to innovative use. This confirms that the more the tasks of management accountants are complex, the more the use of innovative features of the BI system increases. This supports the importance of using the innovative features of the BI system to support task complexity.

6.3 Discussion

The purpose of this chapter was to understand the system success factors influencing the individual use of BI systems with a focus on both routine and innovative use, and their implications for individual performance. More specifically, to address RQ1, which is to examine factors explaining observed variation in the innovative use of BI systems by individual management accountants, this chapter identified and empirically examined four factors explaining observed variation in the innovative use of BI systems by individual management accountants. In addition, to address RQ2 , which is to examine the impact of innovative use of BI systems on the individual-level performance of management accountants, the chapter examined the impact of innovative use of BI systems on the individual-level performance of management accountants. To do so, a BI system success model was developed and empirically tested. The DeLone and McLean (D&M) IS Success Model provided the initial underpinning for the model's development. Data was collected from individual management accountants from the private and public companies in South Africa. The study extended the conceptualisation of system usage to include both routine and innovative use dimensions and obtained the South African BI system user's perspective on BI system success factors through a large sample survey. The AMOS test results presented in Figure 23 and Table 30 indicate that system quality, data quality, information quality and service quality are important factors that influence the type of use of the BI system and improvement in user satisfaction and job performance. The results are discussed in the next section in detail.

6.3.1 Factors Influencing the BI System Use

The results provided answers to the question of which factors may influence the innovative use, routine use, and user satisfaction of the BI system.

The influence of the BI systems success factors are summarised as follows:

BI System Success Factor	Routine Use	Innovative Use	User Satisfaction
System quality	Yes	Yes	Yes
Data quality	Yes	Yes	Yes
Information quality	Yes	Yes	No
Service quality	Yes	Yes	Negative

Within the original D&M IS success model, only two system attributes were considered important components of IS success. These were system quality and information quality (Delone and McLean, 1992). Later, D&M added the concept of service quality (Delone and McLean, 2003). These three attributes have been widely examined as important system attributes leading to overall IS success. Yet, they have been inadequately studied in the BI context (Mudzana and Maharaj, 2017; Yakubu and Dasuki, 2018; Schierder and Gluchowski, 2011, Dinter, Schieder and Gluchowski, 2011; Montero, 2019). Moreover, given that the emphasis of a BI system is on gathering, managing, analysing, and sharing information about the external and internal environment to gain insights for better decision making, this study has contributed a fourth dimension in the form of data quality.

System quality was found to be one of the factors that influence the innovative use of the BI system. System quality measures the usability, availability, reliability, adaptability, portability, integration, and response time of the BI system (Delone and McLean, 1992, 2003; Petter et al., 2008). Most respondents find high system quality and they strongly agree that the BI system is easy to use and stable. The system quality is found to be one of the factors influencing the innovate use of the BI system. Ensuring the BI system is easy to use, friendly and has better response times will assist in improving the innovative use of the system (Serumaga-Zake, 2017). The user's perception that BI system quality has a positive impact on routine and innovative use has been supported. Moreover, the hypothesis that the perception of BI system quality has a positive impact on user satisfaction has also been supported. Therefore, both Ha1 and Ha2 hypothesis were empirically supported on the model. This was expected as previous studies (Popovič et al., 2012; Wixom and Watson, 2010; Tam and Oliveira, 2017) identify system quality as one of the key attributes of system success, leading to system use. The result is now also supported in the BI system context.

Data quality refers to data that is accurate and complete and existing data records are never missing (Torres and Sidorova, 2019). The quality of data was found to be an essential system success factor in the BI context and was found to have a significant influence on both the routine and innovative use of the BI system. Data quality ensures that data records can be used by individual management accountants in executing their tasks (i.e., planning and controlling). Data quality may be an especially important factor in motivating users towards the use of the BI system innovatively. If data is believed to be incomplete and not accurate, then users will not rely on the system in new and creative ways in performing their work. The hypothesis that improvement in data quality may result in user satisfaction was also supported by the model tested (Figure 23). The inclusion of data quality on the BI success model was crucial in ensuring that the model included both input and output of data. Most previous models that measure information system success factors exclude data quality and focus only on information quality (Delone and McLean, 1992, 2003). However, Lautenbach et al. (2017) stated that efforts to improve data quality should be encouraged, and data quality has been considered an essential attribute for BI systems (Torres and Sidorova, 2019). The inclusion of data quality will ensure that users are more likely to use the system innovatively if data stored is trusted to be of a good standard and this may improve user satisfaction (Chen, 2010). Therefore, both Ha3 and Ha4 hypotheses were empirically supported by the model (Figure 23).

Information quality refers to the user's perception that the information outputs of the systems, such as reports, are well formatted, sufficiently detailed, and easy to use for decision making (Torres and Sidorova, 2019). This system quality attribute was found to be a factor that influences both the routine and innovative use of the BI system. Hence, Ha5a and Ha5b were supported. However, the hypothesis linking information quality to user satisfaction was not supported and Ha6 was rejected. Information quality thus appears to be essential to motivating system usage behaviours but is not necessarily important to user satisfaction. This result was not expected as previous studies (Delone and McLean, 1992; 2003; Torres and Sidorova, 2019) in the context of information system confirm the relationship between information quality and user satisfaction. It might be that information quality is a hygiene factor in BI systems. Users expect high quality outputs that meet their information needs (Yakubu and Dasuki, 2018). They are therefore a necessary quality for a BI system. Poor information quality is considered a threat to performing management accounting functions (Rom and Rohde, 2006). Organisations must ensure they design the format of information outputs, to make them easier to understand and to be more consistent for users. This is important in ensuring BI system use. Information might be useful for a particular task, but if it is not presented in a simplified way, it can become useless to the user (Laumer, Christian and Waitzel, 2017). The study also did not measure user *dissatisfaction*. It might be observable that poor quality information outputs lead to dissatisfaction, but good quality information outputs do not necessarily lead to satisfaction. This is an avenue for potential future work to explore.

The final system success factor was service quality. Service quality was found to be one of the factors influencing both the routine and innovative use of the BI system. Hypotheses Ha7a and Ha7b were thus supported. Table 11 indicates that 57% of the respondents have not received formal training in using the BI system. This is a disappointingly low number of respondents as training is a key element of service quality. In ensuring that users will use BI systems innovatively, the BI team should provide a good quality support service. The availability of IS support may assist in ensuring that users gain confidence in using the BI system. Proper support may result in the user using BI systems innovatively. Table 6.20 indicates that service quality received from the IS support team improves innovative and routine use of the system. However, service quality reduces user satisfaction significantly. Ha8 was thus rejected. This was not expected as prior studies (Delone and McLean, 2003; Popovič et al., 2014; Ameen et al., 2020) produce positive significant results. This finding could mean that users that often tend to rely on the team that is supporting the BI system would tend to be more dissatisfied with using the system themselves. Therefore, despite their perception that support is high, they resent needing to access support and experience lower satisfaction with the system overall. Complex systems, even if well supported by a responsive team, may not necessarily be found enjoyable to use. Even if users feel that the support team is interested in solving their problems and being responsive to their needs, they will not necessarily feel the systems works the way they want it to. This type of affective response of users to enterprise systems such as BI systems needs further exploration in future research.

6.3.2 The Role of Task Complexity

The research model hypothesized that task complexity was a moderator of the relationships between innovative and routine use and performance, where it was hypothesised that the link between use and performance may be stronger among individuals who have higher task complexity than among users with lower levels of task complexity (Li et al., 2013; Dawson and Van Belle, 2013; Li and Liu, 2019). The direct path from task complexity to innovative use was significant and does reflect that innovative use of BI systems is more likely to be higher among management accountants whose tasks are complex. However, the path from task complexity to routine use was significant. In the moderator test, task complexity was found to have a positive significant moderating effect on both routine use and innovative use and performance. However, task complexity moderate routine use showed less to individual performance and quality of decision making as compared to the innovative use of the BI system. Users facing less complex task only need routine features and functions, while users facing more complex tasks will rely on more innovative features in their BI usage. Use of the innovative features is required to find solutions to more complex decision problems. As task complexity increases, users shift from routine toward innovative use. This study contradicts the work of Goodhue and Thompson (1995), who argued that high complexity tasks decrease performance. They suggested that in a complex task environment, the volume of information being processed overwhelms the capacity of users, which would then lead to a decrease in individual performance. This study, however, indicates that task complexity can be supported by innovative use of BI systems to achieve high performance outcomes. Thus, this study has made an additional theoretical contribution by demonstrating that task complexity moderates the link between innovative use and individual performance.

6.3.3 The Role of Self-Efficacy

Self-efficacy was introduced as an additional determinant variable in the model influencing routine and innovative use. Self-efficacy provides a judgement on whether an individual can reach their intended goals. It is defined as the belief that the individual possesses the ability to execute the behaviour that assists in enhancing individual performance (Lin et al., 2009), i.e., the ability to use the BI system. Individuals with high self-efficacy are more likely to cope with demanding features of innovative use (Aldholay et al., 2018). It is empirically supported in Figure 30 and Table 23 that individual management accountants who have higher self-efficacy are more likely to use the innovative features of the BI system in performing their task. Self-efficacy is developed through individuals familiarising themselves with the functionality of the BI system. The more they are comfortable with their own ability and have increased self-efficacy, the more likely they are to make more use of the innovative features of a BI system.

6.3.4 Types of Use

Within the D&M IS success model, system use has typically been conceptualised as a single unidimensional construct (Delone and McLean, 2003; Li et al., 2013). The concept of IS use as a single attribute has been widely studied as an important system attribute leading to overall

IS success (Yakubu and Dasuki, 2018; Schierder and Gluchowski, 2011; Popovič et al., 2014). Moreover, given that the emphasis of BI systems use is about measuring the type and intensity of the utilization of the BI solution (Dinter et al., 2011), there is a need to fully understand the type of use that individuals can utilise in the BI systems to improve individual performance. Yet, the distinction between routine and innovative has not been fully understood in the context of the BI system. Drawing on the work of Hajri et al. (2014), this study has contributed by conceptualising use as consisting of both routine use and innovative use.

Routine use of the system is about the use of the basic features of the BI system in performing the function (Hajri et al., 2014; Chen, 2010; Laumer et al., 2016). If users are unable to use the advanced features of the BI system, they would normally be using the system routinely in support of their work. Routine use contributes less to individual performance and quality of decision making as compared to the innovative use of the BI system. This was expected to be the case as routine means the basic use of the BI system by individual management accountants. The important routine use features that are used by management accountants were found to be the following features: existing reports, existing queries, basic analysis, use of Excel, *ad hoc* reporting and data cleansing. The results of the study found that both routine use and innovative use are important to performance but that innovative use has a stronger path coefficient and future research should continue to distinguish between the two.

Innovative use is the critical element of supporting the management accountants in their job performance and quality of decision making (Chen and Cheng, 2009; Hajri et al., 2014; Chen, 2010; Sun and Teng, 2017). This study found that without innovative use of the features of the BI system, individual performance and quality of decision making is less likely to be achieved. In order for the individual management accountants to achieve job performance and decision-making effectiveness, they may need to start to use the advanced features of the BI system. The advanced features found by this study to contribute to improvement in individual performance are predictive analytics, interactive visualisation, drill down functions, dashboard reporting, self-service tool, and predictive modelling. Without these advanced features, it will be a challenge to achieve innovative use of the BI system (Sun and Teng, 2017). In improving their innovative use of the BI system, management accountants should start to focus on scenario planning, agile visualisation, optimisation, query construction and trends analysis. These emerging features of BI systems must be made accessible to management accountants. This study found that the inability to use these features of the BI system to achieve innovative use will affect productivity and the quality of decision making. This is a new contribution of this thesis as previous (Delone and McLean, 2003; Wang et al., 2007; Chen, 2010; Hou, 2012; Li and Liu, 2019; Aldholay et al., 2018) studies did not distinguish the type of use when measuring the BI success factors. Distinguishing between the types of use is important as the users will then know the way in which they must use the system in improving their individual performance.

6.3.5 User Satisfaction

Within the D&M IS success model, user satisfaction is an intermediary system success factor linking the attributes of the system (e.g., system and information quality) to use and benefits thereof. User satisfaction is in a reciprocal relationship with use whereby the user's attitude toward the system is measured against the expectations (Serumaga-Zake, 2017). The user's perception towards the system has been widely studied, considering the net benefits derived from the use of the BI system (Wierder and Ossimitz, 2015; Cohen et al., 2016; Gonzales and Wareham, 2019). The user satisfaction put emphasis on user experience towards the BI system against the expected outcome. However, the impact that innovative use of the BI system has on user's satisfaction needs to be understood in the context of the BI system. Understanding the impact that innovative use of BI systems has on user satisfaction is an additional contribution of this study.

In this study, the initial model hypothesised that user satisfaction would increase innovative use (Ha13). However, this was not tested as it was dropped. The Ha13 was dropped during the process of model improvement as it was contributing to poor model fit.

Innovative use of the BI system is likely to improve user satisfaction. Like the D&M IS success model (DeLone and McLean, 2003; Montero, 2019), use was perceived to have an influence on user satisfaction. Individuals who are likely to be satisfied with the BI system are those who use the BI system innovatively. System use is critical in user satisfaction as it measures the extent, nature, quality, and the appropriateness of using the system. The nature of use then determines if the system is being used for its intended purpose. The extent of use then explains functionalities that are being used, some users only use the routine features while others use innovative features. The type of the use is important on the individual user's satisfaction. The decrease in usage can be an indication that the system is not performing the way it was intended and user satisfaction may be affected, future studies can investigate this impact (DeLone and McLean, 2003; Ain et al., 2019). The reciprocal effects of user satisfaction on innovative use of the BI system could not be fully explored here, hence it was removed on the model. The link between satisfaction to innovative use is however explored in the longitudinal study in the next chapter.

User satisfaction contributes positively to improvement in individual performance. If management accountants enjoying using the BI system, it will be perceived as contributing to their productivity, effectiveness and quality of decision making. User satisfaction is regarded as an attitude that the user has about a particular information system (Wang et al., 2007: Angelina et al., 2019), whilst high usage of the IS system reflects an increase in usage and better quality of the users work life (Yakubu and Dasuki, 2018; Dinter et al., 2011). User satisfaction has been supported as one of the important elements of the BI system that has an influence on improvement on individual performance. User satisfaction can be sustained by maintaining the system's ease of use and continuing to ensure that data is of a high quality. The mean for user satisfaction was lower than for other constructs in the research model. This suggests many management accountant users are not always satisfied with their BI systems. This is a problem that has been recognised by others (e.g., Elbashir et al., 2021; Narayanan and Boyce, 2019). As this study shows, low sastifaction will limit usage and consequent performance. Thus, it is important to continue to explore factors that account for low satisfaction and mitigate those in BI implementations.

6.3.6 Individual Performance

The D&M IS success model includes net benefits of system use as the eventual outcome of an IS system's use. These benefits are considered both at the individual level and the aggregate organisational level. Net benefits measure the comprehensive impact of using an IS system on its users and it was regarded as the most important success factor by DeLone and McLean (2003). Petter et al. (2008) stated that the higher the net benefits, the more the system would be used and thus, improve user satisfaction. For this study, the outcome was individual performance of the management accountant as the BI user. Individual performance was defined as the management accountant's perception of the extent to which the BI system was increasing their work productivity, decision making effectiveness, performance and problem solving (Hou, 2012; Igbaria and Tan,1997). Innovative use of the BI system was found to be a significant factor that improves the contribution of BI to individual performance. The improvement can, however, only happen if the data quality is complete and accurate. In addition, the results found that system quality is also a critical factor in ensuring that the innovative use of the BI system is achieved and translates to individual performance. This was expected as previous studies found that system quality is an important attribute in the overall IS success model (Hajri et al., 2014; Hou, 2012; Delone and McLean, 2003; Saavedra and Bach, 2017; Angelina et al., 2019; Montero, 2019). The D&M IS success model explains the success of the IS system in terms of system quality, information quality and service quality. These attributes affect user satisfaction and system use, which then translate to certain individual and organisational benefits (net benefits) (Delone and McLean, 2003). In addition, without quality of information output, such as completeness and accuracy of reports from the BI system, improvements in individual performance are also not possible. Moreover, it is also crucial that users are supported by a competent team in ensuring that they use the BI system innovatively to improve their performance. The role of the BI system in improving decision-making quality and speed were found to be critical indicators of the improvement in individual performance. This means that individuals through their use of BI can spend less time in meetings, while they focus more on analysing information produced by the BI system. It is evident that management accountants should focus on using the BI system in assisting them with problem identification if they still want to continue with the improvement in their individual performance. If attention is not given to problem solving, this may result in management accountants spending most of their time in problem solving rather than the productive work that they are performing. Individual performance therefore includes both the impacts of BI on decision making and job productivity. Management accountants are in the position to improve their productivity and decision making when using the BI system. This is critical as it then justifies the investments that the organisations are making in implementing the BI system, and the individual investment of time and intellectual effort required to learn to use the more advanced features of the BI system. This is also an additional contribution of this thesis as previous studies drawing on the D&M IS success model have not explained individual level use and performance in the management accounting context. Studies have been conducted in areas such as nursing, education, and marketing environments where individual users are not IT professionals but domain users (e.g., Cohen et al., 2016; Courtois et al., 2014; Chen, 2010; Chen and Cheng, 2009; Isaac et al., 2017; Gaardboe et al., 2017; Angelina et al., 2019). Therefore, D&M IS success model may also be relevant in the management accounting context where individual management accountants represent the domain or community of users of BI systems (e.g., Tomic, 2006; Hou, 2012; Nadia, 2014; Montero, 2019). BI systems should continue to be developed for the use of management accountants.

6.4 Conclusion

This chapter focused on the influence of BI system characteristics on BI system use and its implications for individual performance of management accountants in the South African context. This chapter presented the detailed interpretation of the key findings of the structural model on individual use of the BI system and provide an answer to RQ1 and RQ2. Innovative use was defined to occur when users can use more advanced BI system features such as self-service tools, interactive visualization, predictive analytics, and drill down functionality to support their work and improve their individual performance (Li et al., 2013). The chapter has found, through analysis of responses from 363 management accountants in South Africa, that the factors influencing the innovative use of the BI system are system quality, data quality, information quality and service quality, along with self-efficacy and task complexity. The chapter has also distinguished routine use from innovative use and determined that routine use is less likely under conditions of task complexity and does not rely on self-efficacy to the same extent as innovative use. “The attributes of system quality, data quality, information quality and service quality are nonetheless importance factors that also influence the routine use of the BI system”.

The chapter has also addressed the question of the impact of “innovative use” of the BI system, over and above routine use, on individual performance of management accountants. Results indicate that innovative use is significant for individual performance improving productivity and decision-making effectiveness.

The study presented in this chapter has made an important contribution by differentiating the type of use. Innovative use is the critical element of supporting the management accountants in their job performance and quality of decision making. This study found that without innovative use of the features of the BI system, individual performance and quality of decision making cannot be achieved. For individual management accountants to achieve job performance and decision making, they need to use the advanced features of the BI system. If users are unable to use the advanced features of the BI system, they would normally be using the system routinely in support of their work. Routine use contributes less to individual performance and quality of decision making as compared to the innovative use of the BI system. This was expected to be the case as routine functions limit individual management accountants to only the basic use of a BI system.

Further, the chapter has extended the D&M IS success model by considering the differing information needs of users. These differences in information needs arise from variations in the task complexity of the user. Users facing fewer complex tasks only need routine features and functions, while users facing more complex tasks will rely on more innovative features in their BI usage. Innovative features will help with finding solutions to more complex decision problems, while the routine functions will not. As task complexity increases, users shift from routine toward innovative use. Performance increases when task complexity is supported by innovative use. Self-efficacy was also introduced as an additional determinant variable in the model influencing routine and innovative use. It was empirically supported that individual management accountants who have higher self-efficacy are more likely to use the innovative features of the BI system in performing their task. Thus, the innovative use of the BI system features has been confirmed as a function of system attributes (system, data, information, and service quality), individual user attributes (self-efficacy), and characteristics of the management accountant's job (task complexity).

This chapter focused on the cross-sectional result of the impact and use of the BI system by individual management accountants. The next chapter presents results of the longitudinal study of management accountants who have been using the BI system for less than one year.

CHAPTER 7: THE CROSS-LAGGED EFFECTS OF INNOVATIVE USE OF BI SYSTEMS AND INDIVIDUAL PERFORMANCE

7.1 Empirical Results

In Chapter 6, the factors influencing the innovative use of the BI system were established. In addition, the impact of innovative use of BI systems on the individual-level performance of management accountants was analysed, using cross-sectional data. This Chapter analyses data collected from the empirical study, using the longitudinal data. The RQ2 and RO2 "*To examine the impact of innovative use of BI systems on the individual-level performance of management accountants*" is investigated and empirically tested using longitudinal data. A survey was conducted by means of distributing questionnaires to obtain opinions from individual management accountants who have been using the BI system for two years or less in South Africa. The data was collected over three waves (W_1, W_2 and W_3). Data for W_2 was collected after 12 weeks (three months), while data for W_3 was collected after 16 weeks (four months). The data collected from individual management accountants was used to test the causal relationships of hypothesised cross-lagged individual BI system success models. The initial sections of this chapter discuss the sample size, demographics of the respondents, data screening and sample outliers. In addition, the next sections present descriptive statistics, assessment of normality and sample adequacy of the empirical data analysed. Furthermore, the principal component analysis, reliability and validity, and correlation matrix are performed before the results of the three models are analysed. Finally, the results of the three models, discussion and conclusion are presented.

7.1.1 Sample Size

The first-round survey was sent to 1000 individual management accountants to participate in the study. A total of 365 (a response rate = 36.5%) individual Management Accountants participated in the first-round study where data was collected. This first round dataset was used in the cross-sectional study of BI use (refer to Chapter 6). Of the 365 responses obtained, 94 responses were identified as individual Management Accountants who have been using BI systems for less than two years in their current organisation. These 94 responses constitute the first wave (W_1) dataset for the purposes of this chapter. After 12 weeks (three months), the second round of data was collected. The 94 participants were invited to be part of the second wave (W_2) of the survey. A total of 72 (a response rate =76.6%) individual Management

Accountants participated in the second wave. However, "six responses were eliminated as they were missing a large number of data items". "The final useable W_2 sample thus consisted of 66 observations with sufficient data for meaningful statistical analysis", resulting in a response rate of 70.2%. This suggests a substantial attrition rate of 29.8% in the second wave.

After a further 16 weeks (four months), the third round of data was collected. The 66 participants were invited to be part of the third wave (W_3) of the survey. A total of 61 (a response rate = 64.9%) individual Management Accountants participated in the third wave. However, "two responses were eliminated as they were missing a large number of data items". The "final useable W_3 sample thus consisted of 59 observations with sufficient data for meaningful statistical analysis", resulting in a response rate of 62.7%. This suggests a high attrition rate of 37.2% in the third wave. Wave one (W_1) was matched with Wave two (W_2) and Wave three (W_3) data for each responding Management Accountant using unique self-generated identification codes.

7.1.2 Demographics

Before testing the SEM model using the collected data, descriptive statistics are presented to provide an overview of the sample under study. The demographic profile of the respondents is presented below in Table 33. All 59 useable respondents provided their demographic information.

The results in Table 33 indicate that respondents who are aged between 30 and 35 years old (22.0%) were the highest category of age group, and 45.8% of the respondents were female. The results also indicate the following maximum percentages: 33.9% have 6-10 years' experience in management accounting, 32.2% have 6-10 years of experience in their current organisations, 25.6% 6-10 years business intelligence system experience. Most respondents currently work on SAP business object (52.5%), 84.8% have less than 1 year of business intelligence experience at their organisation. Results further indicate that most of the employees have not attended formal BI training (62.7%), their sector of work is diverse and a slightly higher percentage work in manufacturing sector (18.6%). In addition, 33.9% of the respondents hold a senior management position. Most of the respondents have a professional affiliation with the Chartered Institute of Management Accountants (CIMA) (54.2%).

Table 33 Demographics

Demographics	Category	Frequency	Percentage
Age	18-24 years	8	13,56
	25-29 years	9	15,25
	30-35 years	13	22,03
	36-40 years	9	15,25
	41-45 years	6	10,17
	46-50 years	4	6,78
	51-55 years	8	13,56
	> 55 years	2	3,39
Gender	Male	23	38,98
	Female	27	45,76
	Prefer not to say	9	15,25
Total experience in management accounting	<2 years	8	13,56
	2-5 years	11	18,64
	6-10 years	20	33,90
	11-15 years	9	15,25
	16-20 years	6	10,17
	>21 years	3	5,08
	Prefer not to say	2	3,39
Experience in management accounting at the current company	<2 years	5	8,47
	2-5 years	15	25,42
	6-10 years	19	32,20
	11-15 years	13	22,03
	16-20 years	4	6,78
	>21 years	3	5,08
Total experience in using the BI systems	<2 years	26	44,07
	2-5 years	25	42,37
	6-10 years	6	10,17
	11-15 years	1	1,69
	16-20 years	1	1,69
Current BI system being used by your organisation	SAP business object	31	52,54
	SAS	5	8,47
	Oracle	6	10,17
	Microsoft Suite	9	15,25
	SAGE	7	11,86
	Clear Analytics (Excel based)	1	1,69
BI system experience at current organisation	<1 year	50	84,75
	1-2 years	9	15,25
Training for this BI system attended	Yes	15	25,42
	No	37	62,71
	Prefer not to say	7	11,86
Sector of current employment as management accountant	Manufacturing	11	18,64
	Utilities and energy	6	10,17
	Logistics	4	6,78
	Retail	2	3,39
	Telecoms	5	8,47

Demographics	Category	Frequency	Percentage
	Airline	2	3,39
	Pharmaceutical	4	6,78
	Public sector	6	10,17
	Service	3	5,08
	Finance	6	10,17
	Mining	3	5,08
	Accounting	7	11,86
Current management level	Junior	8	13,56
	Entry management	9	15,25
	Middle Management	13	22,03
	Senior Manager	20	33,90
	Specialist	9	15,25
Professional qualification	CIMA	32	54,24
	SAICA	17	28,81
	Other	10	16,95

Overall, the demographic data suggests that respondents cover many organisations across various industries, they are representative of professionally registered Management Accountants, with sufficient years' experience at high managerial levels. The sample of Management Accountants also occupy high positions in their organisations. The proportion of female respondents is somewhat in line with CIMA membership which is reported to be 49% female. Not all respondents were formally trained on BI systems and the usage experience of all respondents is less than two years and mostly less than one year. The sample is considered appropriate for testing the longitudinal model of individual use and impacts of BI.

Therefore, data analysis could proceed to the next step.

7.1.3 Data Screening

Data collected were analysed using the "Statistical Package for the Social Sciences (SPSS) Version 25" screened for missing data. There were two responses in W_2, and W_3 had one response with a few data items missing. The items affected were routine use, user satisfaction, and individual performance (Table 34). The missing data were handled using the median of nearby points method. The median of the nearby points method is calculated using the average of the nearby surrounding values (Byrne, 2013). "These numbers are calculated using a span of nearby points option in the SPSS program". The median is computed considering all values of the items construct data from the upper and lower, the calculated value is used to replace the missing value (Hair et al., 2010).

Table 34 Responses with Missing Data

Item	Number of missing responses (W_2)	Number of missing responses (W_3)
Routine use (RU) item 3	1	
User satisfaction (US) item 5		1
Individual performance (IP) item 7	1	

7.1.4 Sample Outliers

Outliers are defined as data points that differs significantly from other observations (Hair et al., 2010). To identify potential outliers, any responses that are unusually high or unusually low values were screened (Tarka, 2018). Extreme responses might suggest that the respondents are not from the same population. The extreme values are typically a response with more than three standard deviations above or below the sample mean (Hair et al., 2010). Standardised scores on an item reflect the number of standard deviations from the mean. The standardised scores of each respondent was examined on each questionnaire item and none were identified as outliers. This is not surprising given that the questionnaire items were all answered on a given scale.

7.1.5 Descriptive Statistics

The constructs investigated in this study were measured using two different scales. Firstly, the constructs of user satisfaction and individual performance were measured on seven-point Likert scales where the value of 1 corresponds to “Strongly disagree” and the value of 7 corresponds to “Strongly Agree”. Secondly, the remaining constructs of routine use and innovative use were measured using six-point Likert scales where the value of 1 corresponds to “Never” and the value of 6 corresponds to “Very often”. The mid-point of the seven-point Likert scale is therefore “4”. Thus, all the mean values below 4 suggests that respondents tended to disagree with the statements, whilevalues at 4 indicate a more neutral response. Means above 4 reflect the tendency to agree with the statements. The mean and standard deviation has been presented below (Table 35). The data is only on the matched 59 responses for all waves.

Table 35 Summary of Descriptive Statistics

Wave 1			Wave 2		Wave 3	
Variables	**Mean**	**Std. deviation**	**Mean**	**Std. deviation**	**Mean**	**Std. deviation**
User satisfaction (US)	3,60	1,72	3,45	1,57	3,82	1,68
Individual performance (IP)	5,67	1,03	5,12	1,50	4,82	1,55
Routine use (RU)	4,06	1,36	3,79	1,34	3,38	1,30
Innovative use (IU)	5,08	1,10	4,43	1,25	4,27	1,26

* calculation for each variable based on inclusion of all original measurement items weighted equally to derive a composite score.

7.1.5.1 User satisfaction (US)

The user satisfaction construct is conceptualised as the individual management accountant's beliefs that as a user, they are satisfied overall with the use of the BI system, the system works the way they want it to, and they enjoy using it. The overall means are 3.60; 3.45 and 3.82 for W_1, W_2 and $W_{3,}$ respectively., while the standard deviations are 1.72; 1.57 and 1.68 as presented in Table 35. This suggests that most respondents tend to be neutral or somewhat unsatisfied with the use of the BI system. Five items for user satisfaction were adopted from prior work related with attributes of IS use (Popovič et al., 2012; Hajri et al., 2014), and "measured using a 7-point Likert scale". As illustrated in Table 36, the mean of items ranges from 3.51 to 3.78 for W_1. The mean of items for W_2 ranges from 3.32 to 3.58, while the mean of items for W_3 ranges from 3.68 to 3.92. This suggests that respondents tend not to be overly satisfied with the use of BI systems across the three waves. Results show that items are not significantly different from W1 to W2. This suggests that satisfaction appears to remain relatively stable in early phases of use, if not slightly lower in W2. However, items are significantly higher in W3 than W2 suggesting a slight increase in satisfaction over time, but overall satisfaction remains low relative to the 7-point scale.

Table 36 Statistical Results of US Items

Wave 1			Wave 2		Wave 3		W1vW2	W2vsW3
Variables	**Mean**	**Std. deviation**	**Mean**	**Std. deviation**	**Mean**	**Std. deviation**	**Paired sample t-test**	**Paired sample t-test**
US1	**3,63**	1.77	**3.42**	1.71	**3.78**	1.89	t=0.626 (n/s)	Tt=1.954 (n/s)
US2	**3.53**	1.93	**3.32**	1.71	**3.68**	1.88	t=0.624 (n/s)	t=2.087 (P<0.05)
US3	**3.80**	1.90	**3.58**	1.79	**3.92**	1.91	t=0.661 (n/s)	t=1.991 (P<0.05)
US4	**3.54**	1.97	**3.44**	1.61	**3.88**	1.68	t=0.372 (n/s)	t=2.430 (P<0.05)
US5	**3.51**	1.88	**3.47**	1.65	**3.83**	1.69	t=0.119 (n/s)	t=1.972 (P<0.05)

7.1.5.2 Individual performance (IP)

Individual performance is constructed to extract information on individual management accountants' beliefs that the use of their BI system improves their job performance, productivity and quality of decision making. The overall means are 5.67; 5.12 and 4.82 for W_1, W_2 and W_3, respectively, while the standard deviations are 1.03; 1.50 and 1.55 as presented in Table 35 above. This suggests that most respondents tend to agree that the use of BI improves job performance, productivity and decision making. Seven items were adopted from the work related to individual performance from IS use (Hou, 2012; Igbaria and Tan,1997) and were "measured using 7-point Likert scale". As illustrated in Table 37, the mean of items ranges from 5.59 to 5.81 for W_1. The mean of items for W_2 ranges from 5.03 to 5.22, while the mean of items for W_3 ranges from 4.73 to 4.93. This suggests that respondents tend to be more certain that use of BI systems contributes to their individual performance in the early stages, but this was not sustained across the three waves. Results indicate that most items are significantly lower in W2 compared to W1. In addition, items are significantly lower in W3 from W2. This suggest that initial excitement about performance improvements appear to fall off as users gain more exposure to the system.

Table 37 Statistical Results of IP Items

Wave 1			Wave 2		Wave 3		W1vsW2	W2vsW3
Variables	Mean	Std. deviation	Mean	Std. deviation	Mean	Std. deviation	Paired sample t-test	Paired sample t-test
IP1	**5.59**	1.18	**5.22**	1.69	**4.88**	**1.68**	t=1.333 (n/s)	t=2.257 (P<0.05)
IP2	**5.68**	1.32	**5.03**	1.62	**4.75**	**1.72**	t=2.144 (P<0.05)	t=2.250 (P<0.05)
IP3	**5.58**	1.30	**5.08**	1.71	**4.78**	**1.66**	t=1.675 (n/s)	t=1.957 (n/s)
IP4	**5.71**	1.37	**5.14**	1.74	**4.85**	**1.71**	t=1.992 (P<0.05)	t=2.073 (P<0.05)
IP5	**5.66**	1.29	**5.07**	1.74	**4.80**	**1.77**	t=2.009 (P<0.05)	t=2.126 (P<0.05)
IP6	**5.64**	1.30	**5.22**	1.57	**4.93**	**1.63**	t=1.612 (n/s)	t=2.482 (P<0,05)
IP7	**5.81**	1.31	**5.05**	1.79	**4.73**	**1.87**	t=2.417 (P<0.05)	t=2.877 (P<0.01)

7.1.5.3 Routine use (RU)

Routine use is conceptualised as the use of more basic functions of BI such as standard reports. Individual management accountants were asked to indicate the frequency of their use of these basic features of the BI system. The overall means are 4.06; 3.79 and 3.38 for W_1, W_2 and W_3, respectively, while the standard deviations are 1.36; 1.34 and 130 as presented in Table 35 above. This suggests that respondents tend to occasionally use the basic features of the BI system. Eight items for routine use were adopted from prior work related to IS use (Popovič et al., 2012; Hajri et al., 2014) and "measured using a 6-point Likert scale". As illustrated in Table 38, the mean of items ranges from 3.81 to 4.32 for W_1. The mean of items for W_2 ranges from 3.56 to 3.95, while the mean of items for W_3 ranges from 3.19 to 3.51. This suggests that respondents tend to use routine features occasionally across the three waves. Results show that most items are not significantly different from W_1 to W_2. In addition, items are significantly lower in W_3 compared to W_2. This suggests that routine use appears to fall off over the three waves as users might find routine use less helpful as they gain experience.

Table 38 Statistical Results of RU Items

	Wave 1		Wave 2		Wave 3		W1 vs W2	W2 vs W3
Variables	**Mean**	**Std. deviation**	**Mean**	**Std. deviation**	**Mean**	**Std. deviation**	**Paired sample t-test**	**Paired sample t-test**
RU1	**3.98**	1.44	**3.68**	1.54	**3.27**	1.51	t=1.066 (n/s)	t=3.118 (P<0.01)
RU2	**4.32**	1.54	**3.90**	1.23	**3.51**	1.28	t=1.548 (n/s)	t=2.85 (P<0.01)
RU3	**4.24**	1.52	**3.81**	1.67	**3.42**	1.65	t=1.389 (n/s)	t=2.806 (P<0.01)
RU4	**4.22**	1.55	**3.76**	1.47	**3.39**	1.52	t=1.712 (n/s)	t=2.731 (P<0.01)
RU5	**4.10**	1.56	**3.56**	1.57	**3.19**	1.51	t=1.729 (n/s)	t=2.649 (P<0.01)
RU6	**385**	1.55	**3.93**	1.66	**3.42**	164	t=-0.273 (n/s)	t=3.352 (P<0,001)
RU7	**3.97**	1.56	**3.71**	1.60	**3.34**	1.61	t=0.854 (n/s)	t=2.821 (P<0.01)
RU8	**3.81**	1.89	**3.95**	1.65	**3.51**	1.68	t=-0.369 (n/s)	t=2.986 (P<0.01)

7.1.5.4 Innovative use (IU)

The Innovative use scale was constructed to extract self-reported data on how often individual management accountants use advanced features of the BI system. The overall means are 5.08; 4.43 and 4.27 for W_1, W_2 and W_3, respectively, while the standard deviations are 1.10; 1.25 and 1.26 as presented in Table 35 above. This suggests that most respondents report using more advanced features of the BI system often. Twelve items for innovative use were adopted from prior work related to attributes of IS use (Popovič et al., 2012; Hajri et al., 2014) and "measured using a 6-point Likert scale". As illustrated in Table 39, the mean of items ranges from 4.85 to 5.39 for W_1. The mean of items for W_2 ranges from 4.03 to 4.80, while the mean of items for W_3 ranges from 3.88 to 4.63. This suggests that respondents tend to agree that they use more advanced features of the BI system often. Results indicate that most items are significantly lower in W_2 than W_1. In addition, items are significantly lower in W_3 than what was reported in W_2. This suggests that innovative use appears to fall off over the three waves. However, innovative use still appears more important to management accountants who, on average, seem to use innovative BI features more often to support their work. Both routine and innovative use falls over the period which suggests that respondents do not necessarily substitute their use of basic features for more innovative features. It appears that respondents are initially excited about use and report using more features, more often but later, become less engaged. Subsequent sections explore potential explanations for these observed patterns by testing various cross-lag models.

Table 39 Statistical Results of IU Items

Wave 1			Wave 2		Wave 3		W1 vs W2	W2 vs W3
Variables	**Mean**	**Std. deviation**	**Mean**	**Std. deviation**	**Mean**	**Std. deviation**	**Paired sample t-test**	**Paired sample t-test**
IU1	5.24	1.02	4.49	1.24	4.34	1.23	t=3.672 (P<0.001)	t=3.231 (P<0.01)
IU2	5.08	1.32	4.41	1.51	4.25	1.50	t=2.610 (P<0.01)	t=3.180 (P<0.01)
IU3	5.39	1.05	480	1.23	4.63	1.30	t=2.870 (P<0.01)	t=3.089 (P<0.01)
IU4	5.22	1.42	4.68	1.52	4.53	1.55	t=1.950 (n/s)	t=2.356 (P<0.01)
IU5	5.10	1.23	4.56	1.49	4.41	1.53	t=2.274 (P<0.05)	t=3.364 (P<0.01)
IU6	4.98	1.36	4.03	1.41	3.88	1.39	t=3.623 (P<0.001)	t=2.928 (P<0.05)
IU7	5.07	1.11	4.46	1.24	4.31	1.24	t=2.804 (P<0.01)	t=3.027 (P<0.01)
IU8	4.85	1.36	4.22	1.60	4.07	1.60	t=2.225 (P<0.05)	t=2.834 (P<0.05)
IU9	5.02	0.97	4.41	1.38	4.25	1.45	t=3.154 (P<0.01)	t=3.418 (P<0.001)
IU10	4.97	1.31	4.42	1.56	4.27	1.60	t=2.098 (P<0.05)	t=3.017 (P<0.01)
IU11	5.05	1.09	4.39	1.30	4.24	1.28	t=2.990 (P<0.01)	t=3.304 (P<0.01)
IU12	5.02	1.31	4.27	1.46	4.12	1.40	t=2.869 (P<0.01)	t=3.232 (P<0.01)

7.1.6 Assessment of Normality

Table 40 above, “indicates Skewness and Kurtosis coefficients” of all the constructs appearing in the model. The value for skewness and kurtosis between -2 and +2 is considered an acceptable indication of normality (George and Mallery, 2010). The results summarized in Table 40 indicate an acceptable normality[11] given that the values of most kurtosis and skewness are between -2 and +2 except for individual performance which has a kurtosis of +5 in W_1. However, the central limit theorem stipulates that deviation from the normality has little effect on the data for large sample size (Muzaffar, 2016). This means that the abnormal kurtosis of the variables (items or constructs) exceeding the thresholds of -2 and + 2 will not be of concern in the overall results. Since the normality is not an issue, we can confidently use the principal component analysis to check if the items are loading with the latent constructs.

Table 40 Summary of Skewness and Kurtosis

Wave 1			Wave 2		Wave 3	
Variables	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**	**Skewness**	**Kurtosis**
User satisfaction	0.4700	- 1.4741	0.5986	- 0.8378	0.4067	- 1.4850
Individual performance	- 2.0673	5.1376	- 1.0806	- 0.2247	- 0.5445	- 1.0902
Routine use	- 0.2924	- 1.5295	- 0.1157	- 1.3987	0.4012	- 1.3492
Innovative use	- 1.6820	1.5716	- 1.0430	- 0.3907	- 0.7183	- 0.9153

7.1.7 Sample Adequacy

Prior to proceeding with a principal component analysis (PCA) for the purposes of confirming the validity of the multi-item scales, it is necessary to first establish sample adequacy. The adequacy of the sample is measured using the Kaiser-Meyer-Olkin (KMO) test as developed by Kaiser and Rice (1974). According to Field (2009), the KMO “measures sampling characteristic of the ratio of the squared correlation between variables to the squared partial correlation between variables”. The patterns of correlations vary between 0 to 1, if the value of the correlation is closer to 1, the correlations should produce reliable factors (Field, 2009). The values that are between 0.5 and 0.7 are poor, between 0.7 and 0.8 are good, valued between 0.8 and 0.9 are great, and above 0.9 are excellent (George and Mallery, 2010). The results of the first wave study are illustrated below in Table 41, which indicates the KMO results as 0.815.

[11] Although survey data may sometimes be subject to polarised views, bimodal distributions, J curves and other anomalies, the data distributions were found acceptable.

The results of KMO indicates that the sampling adequacy falls within the acceptable range. This indicate that the sampling size is adequate to yield reliable factors.

Table 41 W_1 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.815
Approx. Chi-Square	1.945
df	378
Sig.	0.000

The results of the second wave study are illustrated below in Table 42, which indicates the KMO results as 0.803. The results of KMO indicates that the sampling adequacy falls within the acceptable range. This indicate that the sampling size is adequate to yield reliable factors. In addition, the Chi-square is 2.315 and its significance is less than 0.001. This indicates that the data of W_2 can usefully be analysed with the PCA analysis.

Table 42 W_2 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.803
Approx. Chi-Square	2.315
df	496
Sig.	0.000

The results of the third wave study are illustrated below in Table 43, which indicates the KMO results as 0.811. The results of KMO indicates that the sampling adequacy falls within the acceptable range. This indicates that the sampling size is adequate to yield the reliable factors.

Table 43 W_3 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.811
Approx. Chi-Square	2.219
df	465
Sig.	0.000

Bartlett (1954) developed a test that analysed whether the correlations between survey items is large enough for appropriate factor analysis. This test indicates the strength of the relationship within variables. The results of the research indicate that the Chi-square is 1.945; 2.315 and 2.219 for W_1, W_2 and W_3 respectively and its significance is less than 0.001. This indicates that the data for W_1, W_2 and W_3 can usefully be analysed with the PCA analysis.

7.1.8 Principal Components Analysis (PCA)

Factor analysis (principal component) was conducted using the orthogonal rotation (Varimax) method. "This method was selected because it essentially captures the components with high eigenvalues and organises by order of importance" (Hair et al., 2011). Factor analysis functions on the assumption that measurable and observable variance can be reduced to a few latent variables that share common variance (Vonglao, 2017). This is known as the reduction of dimensionality. The unobserved factors are not measured directly but they are critical in a hypothetical model. The use of Exploratory Factor Analysis (EFA) is the first step in constructing scales (Hair et al., 2011). EFA is considered a useful first step prior to any Confirmatory Factor Analysis (CFA) at the early-stages of developing the scale. EFA offers an opportunity to a researcher to explore the main dimension to produce a theory or model from latent constructs represented by set of items (Sangthong, 2020). In this study, an exploratory analysis was considered necessary prior to formal model testing as there is not enough research evidence on the use and impacts of BI systems for individual management accountants in the South African context, and therefore an initial exploratory approach was warranted.

Hair et al. (2010) stated that for a construct to be labelled a factor, it should have at least three variables (i.e., scale items), this can also depend on how the study has been designed. The number of factors produced depends on whether the variable might have a relationship with more than one factor (Murray, 2013). The use of a rotation matrix maximises high item loadings, while minimising low item loadings. This produces a more interpretable and simplified solution. The rotation on SPSS can be carried out using five various methods such as varimax, quartimax, equamax, direct oblimin and promax (Sangthong, 2020). This study chose to use varimax rotation to maximise high item loadings. Furthermore, a "factor score coefficient matrix was used in the scores menu and opted for listwise exclusion", "sorting by size and suppression of absolute values less than 0.40 in the options menu". The suppression of absolute values less than 0.40 allows for easier visual interpretation of the loadings. This study used the 59 responses that were linked on all three different waves (W_1, W_2 and W_3), and the factor loading was low at 0.50 or less. Items with loadings of less than 0.50 were eliminated from the study. The factor loadings were calculated on various waves (W_1, W_2 and W_3) as the study is longitudinal in nature. The results of various waves are presented below in a table format (Table 44; Table 45 and Table 46).

Table 44 presents the results of factor analysis on the set of items in relation to W_1. The principal component analysis indicates that four factors were extracted on 28 items. The total variance explained is 81%.

Table 44 W_1 Principal Component Analysis

"Rotated Component Matrix"				
		"Component"		
Items	**1**	**2**	**3**	**4**
US1			.847	
US2			.909	
US3			.910	
US4			.879	
US5			.897	
IP2				.863
IP3				.826
IP6				.834
IP7				.856
RU1		.829		
RU2		.839		
RU3		.875		
RU4		.890		
RU5		.906		
RU6		.836		
RU7		.849		
RU8		.810		
IU1	.906			
IU2	.906			
IU3	.934			
IU4	.950			
IU5	.837			
IU6	.933			
IU7	.866			
IU8	.898			
IU10	.880			
IU11	.831			
IU12	.915			
Rotation Method: Varimax with Kaiser Normalization.				
Rotation converged.				

"Rotated Component Matrix"				
"Component"				
Items	**1**	**2**	**3**	**4**
Total Variance Explained 81%				

User satisfaction (US) in W_1 was measured through five items. As per Table 44, five items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Therefore, all items were retained.

Individual performance (IP) W_1 was measured through seven items. As per Table 44, four items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Three items for individual performance W_1 were dropped which are IP1, IP4 and IP5. These items were dropped because the item loadings were less than 0.50.

Routine use (RU) W_1 was measured through eight items. As per Table 44, eight items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Therefore, no items for routine use needed to be dropped.

Innovative use (IU) W_1 was measured through twelve items. As per Table 44, eleven items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. One item for innovative use was dropped which is IU9. This item was dropped because the item loading was less than 0.50.

The W_1 model consisted of four constructs which was confirmed by the underlying factor structure extracted by the PCA. The analysis could then proceed to examine the factor loadings of W_2.

Table 45 presents the results of factor analysis on the set of items in relation to W_2. The principal component analysis indicate that four factors were extracted on 32 items. The total variance explained is 80%.

Table 45 Principal Component Analysis

"Rotated Component Matrix"				
"Component"				
Items	**1**	**2**	**3**	**4**
US1				.921
US2				.913
US3				.930
US4				.889

"Rotated Component Matrix"				
"Component"				
Items	**1**	**2**	**3**	**4**
US5				.878
IP1			.900	
IP2			.902	
IP3			.872	
IP4			.904	
IP5			.902	
IP6			.881	
IP7			.707	
RU1		.784		
RU2		.816		
RU3		.858		
RU4		.790		
RU5		.862		
RU6		.893		
RU7		.906		
RU8		.846		
IU1	.936			
IU2	.838			
IU3	.915			
IU4	.913			
IU5	.867			
IU6	.889			
IU7	.915			
IU8	.872			
IU9	.875			
IU10	.864			
IU11	.744			
IU12	.858			
Rotation Method: Varimax with Kaiser Normalization.				
Rotation converged.				
Total Variance Explained 80%				

User satisfaction (US) in W_2 was measured through five items. As per Table 45, five items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Therefore, all items were retained.

Individual performance (IP) W_2 was measured through seven items. As per Table 45, seven items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Therefore, all items were retained.

Routine use (RU) W_2 was measured through eight items. As per Table 45, eight items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Therefore, no items for routine use needed to be dropped.

Innovative use (IU) W_2 was measured through twelve items. As per Table 45, twelve items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Therefore, no items for innovative use needed to be dropped.

The W_2 model consisted of four constructs which was confirmed by the underlying factor structure extracted by the PCA. The analysis could then proceed to examine the factor loadings of W_3.

Table 46 presents the results of factor analysis on the set of items in relation to W_3. The principal component analysis indicate that four factors were extracted on 32 items. The total variance explained is 80%.

Table 46 W_3 Principal Component Analysis

"Rotated Component Matrix"				
"Component"				
Items	**1**	**2**	**3**	**4**
US1				.934
US2				.921
US3				.956
US4				.934
US5				.880
IP1		.883		
IP2		.908		
IP3		.840		
IP4		.911		
IP5		.895		
IP6		.887		
IP7		.791		
RU1			.781	
RU2			.831	
RU3			.862	
RU4			.813	
RU5			.816	
RU6			.891	
RU7			.881	
RU8			.800	
IU1	.919			
IU2	.816			

"Rotated Component Matrix"				
"Component"				
Items	**1**	**2**	**3**	**4**
IU3	.908			
IU4	.914			
IU5	.868			
IU6	.892			
IU7	.897			
IU8	.841			
IU9	.861			
IU10	.908			
IU12	.861			
Rotation Method: Varimax with Kaiser Normalization.				
Rotation converged.				
Total Variance Explained 81%				

User satisfaction (US) in W_3 was measured through five items. As per Table 46, five items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Therefore, all items were retained.

Individual performance (IP) W_3 was measured through seven items. As per Table 46, seven items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Therefore, all items were retained.

Routine use (RU) W_3 was measured through eight items. As per Table 46, eight items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. Therefore, no items for routine use needed to be dropped.

Innovative use (IU) W_3 was measured through twelve items. As per Table 46, eleven items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. One item for innovative use was dropped which is IU11. This item was dropped because the item loading was less than 0.50.

Altogether, the model consisted of four constructs which was confirmed by the underlying factor structure extracted by the PCA for both waves (W_1, W_2 and W_3). The analysis could then proceed to examine the reliability of the scales for all three waves (W_1, W_2 and W_3).

7.1.9 Reliability and Validity

It is evident that for the scale to be valid and have practical usefulness, it must be reliable (Byrne, 2013). The reliability is the ability of the scale to produce the same results if it is used in the same conditions with the same objectives (Hair et al., 2010). In this study, the scale used four factors to measure the proposed research conceptual framework, namely user satisfaction, routine use, innovative use, and individual performance. The same four constructs were used for both the three waves (W_1, W_2 and W_3). The indicators in waves may differ slightly due to dropping of some items. Table 47 presents the results of “Cronbach’s alpha”, “Average Variance Extracted (AVE) and Composite Reliability (CR)”. In measuring the reliability, the “Cronbach’s alpha” was used. The scale is regarded as “reliable if the Cronbach’s alpha is 0.70 or higher” (Hair et al., 2010). Table 47 indicates that the “Cronbach’s alpha” ranges from 0.891 to 0.979 for W_1, while W_2 ranges from 0.950 to 0.975 and W_3 ranges from 0.937 to 0.974. This is above the recommended value of 0.70. The CR for both three waves range from 0.826 to 0.978, which is above the threshold of 0.70. In addition, the AVE for each construct was calculated. The AVE for the three waves has a minimum value of 0.697 which is more than the recommended 0.50 threshold.

Table 47 Results of Reliability and Validity

						Composite scores	
Variables	**Number of Initial items**	**Number of surviving items**	**“Cronbach’s alpha”**	**“Average variance extracted (AVE)”**	**“Composite reliability (CR)”**	**Mean**	**Standard deviation**
US1	5	5	0.947	0.790	0.949	3.60	1.72
IP1	7	4	0.891	0.713	0.909	5.68	1.13
RU1	8	8	0.950	0.731	0.843	4.06	1.36
IU1	12	11	0.979	0.804	0.978	5.09	1.13
US2	5	5	0.959	0.822	0.958	3.45	1.57
IP2	7	7	0.954	0.756	0.940	5.12	1.50
RU2	8	8	0.950	0.715	0.844	3.79	1.34
IU2	12	12	0.975	0.766	0.975	4.43	1.25
US3	5	5	0.961	0.856	0.968	3.82	1.68
IP3	7	7	0.964	0.765	0.943	4.82	1.55
RU3	8	8	0.937	0.697	0.826	3.38	1.30
IU3	12	11	0.974	0.776	0.974	4.28	1.29

7.1.10 Comparison of Construct Means

Previous research in information systems has argued that system use may improve over time. Benlian (2015) stated that for the use to be properly understood, there is a need to distinguish the type of use and evaluate the possible improvement over time. This is because later decisions to use the information system are not made from scratch but are a result of earlier decisions to use the information system. However, Iivari (2005) argued that factors promoting early use of an information system diminish over time such that they have little influence on later decisions to use the information system. To determine if individual beliefs are different over time, the means at the three waves were compared using the paired sample t-test. This study used the 59 responses that were linked on all three different waves (W_1, W_2 and W_3). The means were compared as follows; W_1 to W_2; W_2 to W_3 and W_1 to W_3. The mean of US1 to US2 moved from 3.60 to 3.45, however the changes were not statistically significant ($P>0.05$), while the mean of US2 to US3 increased from 3.45 to 3.82. The changes on the mean were statistically significant ($P<0.05$). User are expected to improve their satisfaction over time (Table 48). In addition, the means of US1 to US3 moved from 3.60 to 3.82, however the changes were not statistically significant ($P>0,05$). The mean of IP1 to IP2 decreased from 5.68 to 5.12, however the changes were not statistically significant ($P>0.05$). The mean of IP2 to IP3 dropped from 5.12 to 4.82, however the changes on the means were not statistically significant ($P>0,05$). In addition, the means of IP1 to IP3 dropped from 5.68 to 4.82, and this change was statistically significant ($P<0,001$). Users are reporting lower perceptions of the individual performance impacts of BI over time.

The mean of RU1 to RU2 decreased from 4.06 to 3.79, however the changes were not statistically significant ($P>0.05$). The mean of RU2 to RU3 decreased from 3.79 to 3.38, and the changes on the means were statistically significant ($P<0.001$). In addition, the means of RU1 to RU3 dropped from 4.06 to 3.38, and the changes were also statistically significant ($P<0.05$). Hence, routine use is expected to slightly decrease over time. The mean of IU1 to IU2 decreased from 5.09 to 4.43, with the changes statistically significant ($P<0.05$). The mean of IU2 to IU3 dropped further from 4.43 to 4.28, with the changes on these means also being statistically significant ($P<0.05$). In addition, the means of IU1 to IU3 dropped from 5.09 to 4.28, with the changes statistically significant ($P<0.001$). It seems that over time, users are reducing both their routine and their innovative use. These same users also report a drop in their individual performance, and this is despite user satisfaction being at its highest in W3. As users gets more comfortable with a system over time, routine use is expected to be replaced by more innovative use. It is however not expected that innovative use would decline. While the decline might relate to the specific information requirements of some users at the time of the surveys, it is also plausible that the drop off reflects a common problem with new IS implementations where usage drops off over time as users revert to prior practices and workarounds. These users were all within the first couple years of their organisation's BI implementation and thus the decrease in usage over time may reflect this phenomenon. Tests of the cross-lag model may reveal insights into whether factors such as user satisfaction or a lack of experienced benefits (individual performance) may account for these observed usage behaviours.

Table 48 Comparison of the Means in BI Use, User Satisfaction, and Individual Performance

		Wave1		Wave2		Wave3		Paired differences		t-statistics	P-value	
	N	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.			
US1=US2	59	3.60	1.72	3.45	1.57			0.149	2.102	0.545	0.588	n/s
IP1=IP2	59	5.68	1.13	5.12	1.50			0.560	1.902	2.229	0.300	n/s
RU1=RU2	59	4.06	1.36	3.79	1.34			0.273	2.043	1.028	0.308	n/s
IU1=IU2	59	5.09	1.13	4.43	1.25			0.660	1.644	3.055	**0.003 ****	**Sig lower**
US2=US3	59			3.45	1.57	3.82	1,68	0.369	1.316	2.156	**0.035 ***	**Sig higher**
IP2=IP3	59			5.12	1.50	4.82	1,55	0.300	0.914	2.524	0.140	n/s
RU2=RU3	59			3.79	1.34	3.38	1,3	0.407	0.925	3.377	**0.001 ****	**sig lower**
IU2=IU3	59			4.43	1.25	4.28	1,29	0.150	0.366	3.230	**0.002 ****	**sig lower**
US1=US3	59	3.60	1.72			3.82	1,68	0.220	2.285	0.741	0.462	n/s
IP1=IP3	59	5.68	1.13			4.82	1,55	0.860	1.849	3.540	**0.001 ****	**Sig lower**
RU1=RU3	59	4.06	1.36			3.38	1,3	0.680	2.017	2.590	**0.012 ***	**Sig lower**
IU1=IU3	59	5.09	1.13			4.28	1,29	0.810	1.609	3.857	**0.000*****	**Sig lower**

7.1.11 Correlation Matrix of Composite Scores

"Construct validity" can be assessed through examination of "convergent and discriminant validity" (Sangthong, 2020). The inter-correlations between constructs has been calculated and presented in Table 49. The principle of "discriminant validity" requires that the measures of a construct should correlate more highly with each other and not correlate as highly with measures of other constructs (Hair et al., 2010). This principle can be tested by comparing inter-construct correlations with the "AVE or square root of AVE of each construct". The "square roots of AVE" of each construct are presented along the diagonal of Table 49. These are shown as larger than the inter-construct correlations (Table 49). The "discriminant validity" is thus confirmed i.e., within each wave there is appropriate "discriminant validity" but that there are high correlations between measures of the same construct across waves which is appropriate. Taken together, all these above results then confirm the reliabilities, "convergent and discriminant validities of the constructs". The model can then be tested in the next section.

Table 49 Results of Matrix of Composite Scores

	Mean (S.D.)	US1	IP1	RU1	IU1	US2	IP2	RU2	IU2	US3	IP3	RU3	IU3
US1	3.6 (1.72)	**0.790**											
IP1	5.68 (1.13)	0.237	**0.713**										
RU1	4.06 (1.36)	0.184	0.177	**0.731**									
IU1	5.09 (1,13)	0.304*	0.325*	0.222	**0.804**								
US2	3.45 (1.57)	0.187	-0.079	0.005	0.012	**0.822**							
IP2	5.12 (1.50)	0.317*	-0.103	-0.036	0.313*	0.234	**0.756**						
RU2	3.79 (1.34)	0.320*	0.104	-0.146	0.137	0.265 *	0.236	**0.715**					
IU2	4.43 (1.25)	0.181	-0.061	0.031	0.027	0.195	0,.285*	0.264*	**0.766**				
US3	3.82 (1.68)	0.097	-0.161	0.119	-0.052	0.675**	-0.079	0.111	0.208	**0.856**			
IP3	4.82 (1.55)	0.408 **	0.009	0.016	0.357**	0.325*	0.821**	0.251	0.336**	-0.021	**0.765**		
RU3	3.38 (1.30)	0.235	0.249	-0.150	0.032	-0.003	0.063	0.754**	0.062	-0.088	0.073	**0.697**	
IU3	4.28 (1.29)	0.246	-0.010	0.026	0.077	0.246	0.347**	0.237	0.958**	0.104	0.430 **	0.030	**0.776**

*. "Correlation is significant at the 0.05 level (2-tailed)".

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

7.2 Results of Model Testing

This section uses the data collected to formally test the study's measurement and structural model in detail. It must be emphasised that data was collected over three different waves (W_1, W_2 and W_3). The data collected has been used to test causality of the three different models. The models compare the causal relationships amongst routine use, innovative use, user satisfaction and individual performance. Model one (M_1) was specified as W_1 (RU1, IU1 and US1) to W_2 (IP2), while model two (M_2) tested the causality of W_2 (RU2, IU2 and US2) to W_3 (IP3). Model three (M_3) tested the causality of W_1 (RU1, IU1 and US1) to W_3 (IP3).

Before the hypothesised structural models can be tested, it is advisable to perform CFA for each model as a final test of the measurement model to identify if all the items are loading properly on the hypothesised constructs in the model. The CFA was used to test the hypothesis with respect to sources of variability responsible for the commonality among a set of scores. The CFA analysis of M_1[12] and M_3[13] used only the 31 items measuring the main variables of which one (IU9) was dropped in the exploratory factor analysis (PCA) stage due to low loading. In addition, the CFA analysis of M_2[14] used only the 32 items measuring the main variables of which none was dropped in the exploratory factor analysis (PCA) stage. The CFA was used to confirm that the proposed factor structure is a good fit to the data.

The second step is to use Structural Equation Modelling (SEM) to test the causal relationship of hypotheses represented, i.e., the structural model. The SEM model was conducted using AMOS version 25; AMOS is easier to use as the path diagrams are simplified compare to other software such as LISREL, STATA etc. (Sangthong, 2020).

7.2.1 CFA Model Results

The CFA was used to assess the relationships between various constructs within the developed theoretical model and their measurement items. In assessing the model, it is important to look at the measurement model fit and measure the validity of the model being tested. In the process of evaluating the measurement model in the CFA, there is no need to differentiate between exogenous and endogenous constructs. Differentiating between exogenous and endogenous constructs is only necessary during the model testing. Figures 25, 26 and 27 indicate all variables being linked together and the measured variables (construct items) are shown in rectangular shapes. The covariances are illustrated in Figures 25, 26 and 27 by two headed arrows, the causal relationship is indicated by one-headed arrows. Therefore, the models in Figures 25, 26 and 27 only focus on user satisfaction, innovative use, routine use, and individual performance. The CFA was done for M_1, M_2 and M_3.

7.2.1.1 CFA model 1 results

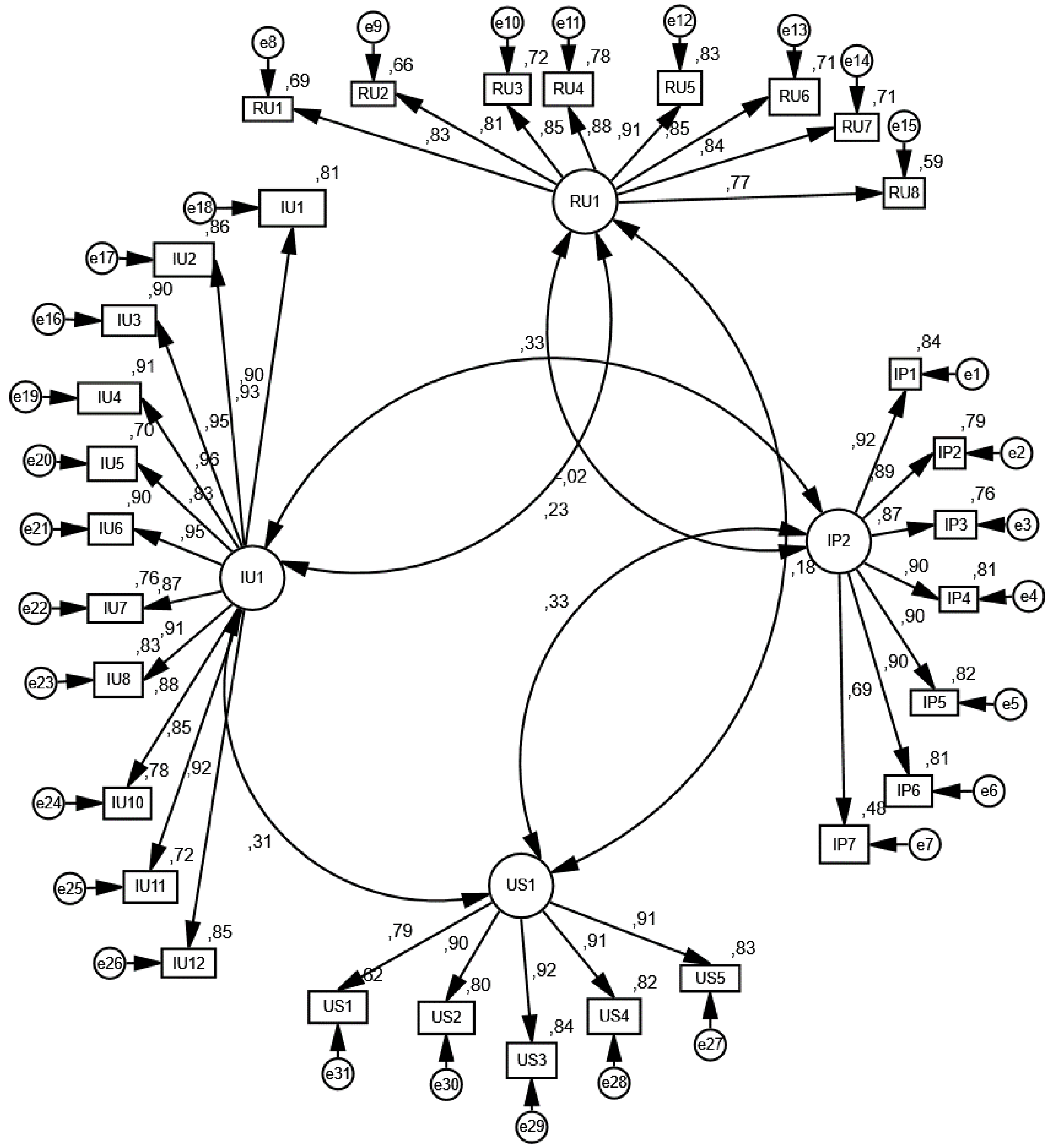
The maximum-likelihood method was adopted to estimate the model's parameters and all analyses were conducted on covariance matrices. There are model fit indices that need to be

[12] M_1 includes routine use at W_1, Innovative use at W_1, User satisfaction at W_1 and individual performance at W_2.
[13] M_3 includes routine use at W_1, Innovative use at W_1, User satisfaction at W_1 and individual performance at W_3.
[14] M_2 includes routine use at W_2, Innovative use at W_2, User satisfaction at W_2 and individual performance at W_3.

considered when analysing the model goodness-of-fit. The first step is to assess the Chi-square (X^2)/ degree of freedom (DF) ratio of the model being tested. The X^2/DF was found to be high, which indicates that the data does not fit the model well. This test may however reject the hypotheses unnecessarily (Hair et al., 2010) as even small differences between the observed model and the good model fit might be found to be significant.

The M_1 X^2/DF on the CFA model is 6 which is greater than 3, this indicates that there is still room for improving the model. The M_1 (routine use W_1, innovative use W_1, user satisfaction W_1 and individual performance W_2) indicates the initial indices as follows (GFI= 0.60; NFI=0.732; CFI=0.863; IFI=0.865; RMSEA=0.113; $P<0.001$; DF=428; TLI=0.851 and RFI=0.709). The validity of the CFA model indicates that some model fit indices were not satisfactory. However, the main objective of the CFA model was to check if all the items of the scale are loading on the model. The CFA test was conducted to confirm construct validity and factor loadings (Serrano Archimi, Reynaud, Yasin and Bhatti, 2018). It was not meant to test the hypotheses among the constructs. The results indicate that all the items are loading appropriately and in line with theory. The factor loadings of M_1 range between 0.692 to 0.956 (Figure 25), which is above the prescribed threshold of 0.50. M_1 examines the effects of RU1, IU1 and US1 on IP2.

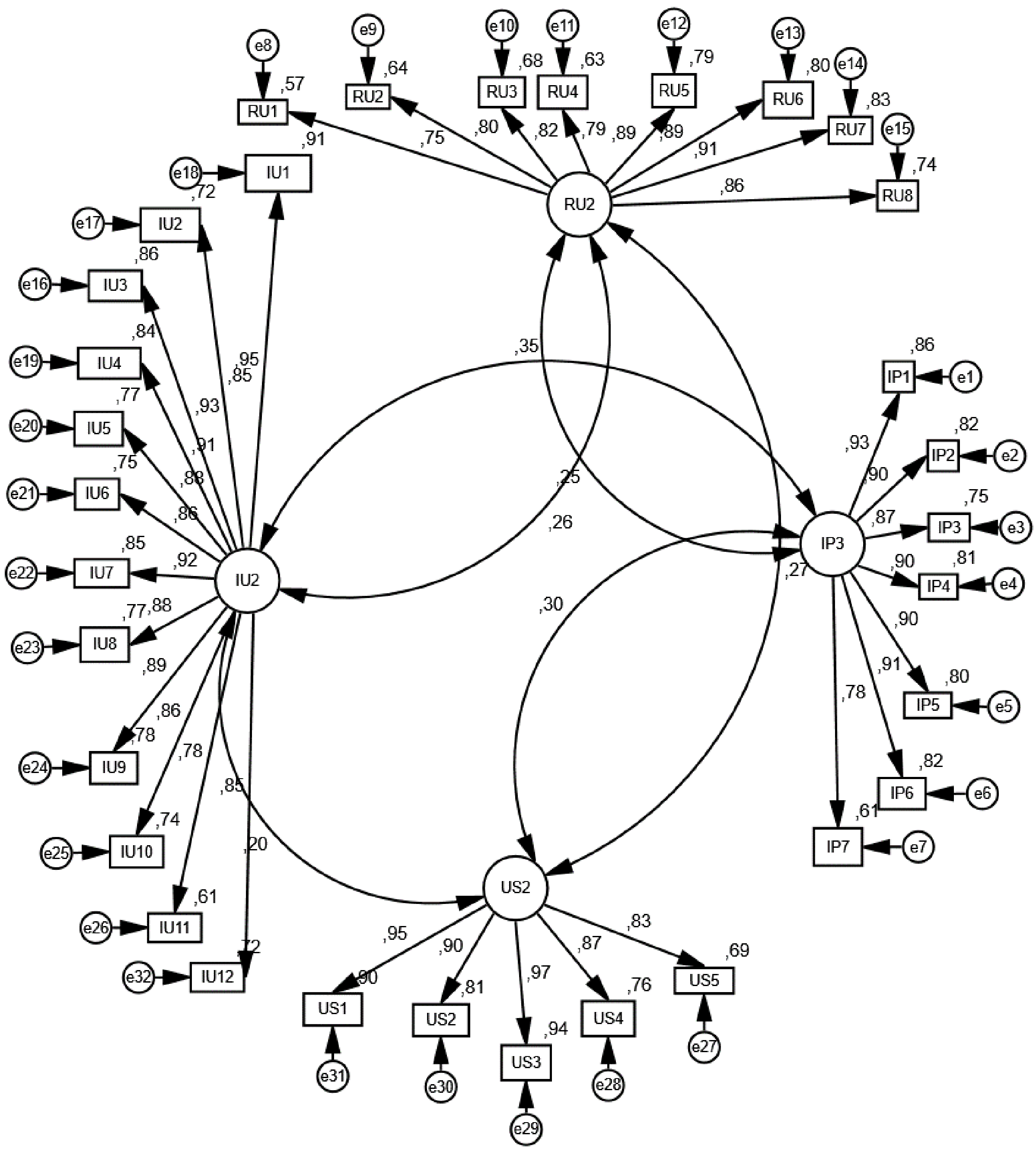
Figure 25 Initial CFA Measurement Model 1 (M1 examines the effects of RU1, IU1 and US1 on IP2)



7.2.1.2 CFA model 2 results

Figure 26 indicates the results of the CFA being tested for M_2 (routine use W_2, innovative use W_2, user satisfaction W_2 and individual performance W_3). The X^2 / DF was found to be high, which indicates that the data does not fit the model well. The M_2 X^2 / DF on the CFA model is 6 which is greater than 3, this indicate that there is still room for improving the model. The M_2 indicates the initial indices as follows (GFI= 0.565; NFI=0.702; CFI=0.829; IFI=0.832; RMSEA=0.126; P<0.001; DF=458; TLI=0.815 and RFI=0.678). The validity of the CFA model indicates that some model fit indices were not satisfactory. However, the main objective of the CFA model was to check if all the items of the scale are loading on the model. The CFA test was conducted to confirm construct validity and factor loadings (Serrano Archimi et al., 2018). The factor loadings of M_2 range between 0.754 to 0.952 (Figure 26), which is above the prescribed threshold of 0.50. M_2 examines the effects of RU2, IU2 and US2 on IP3.

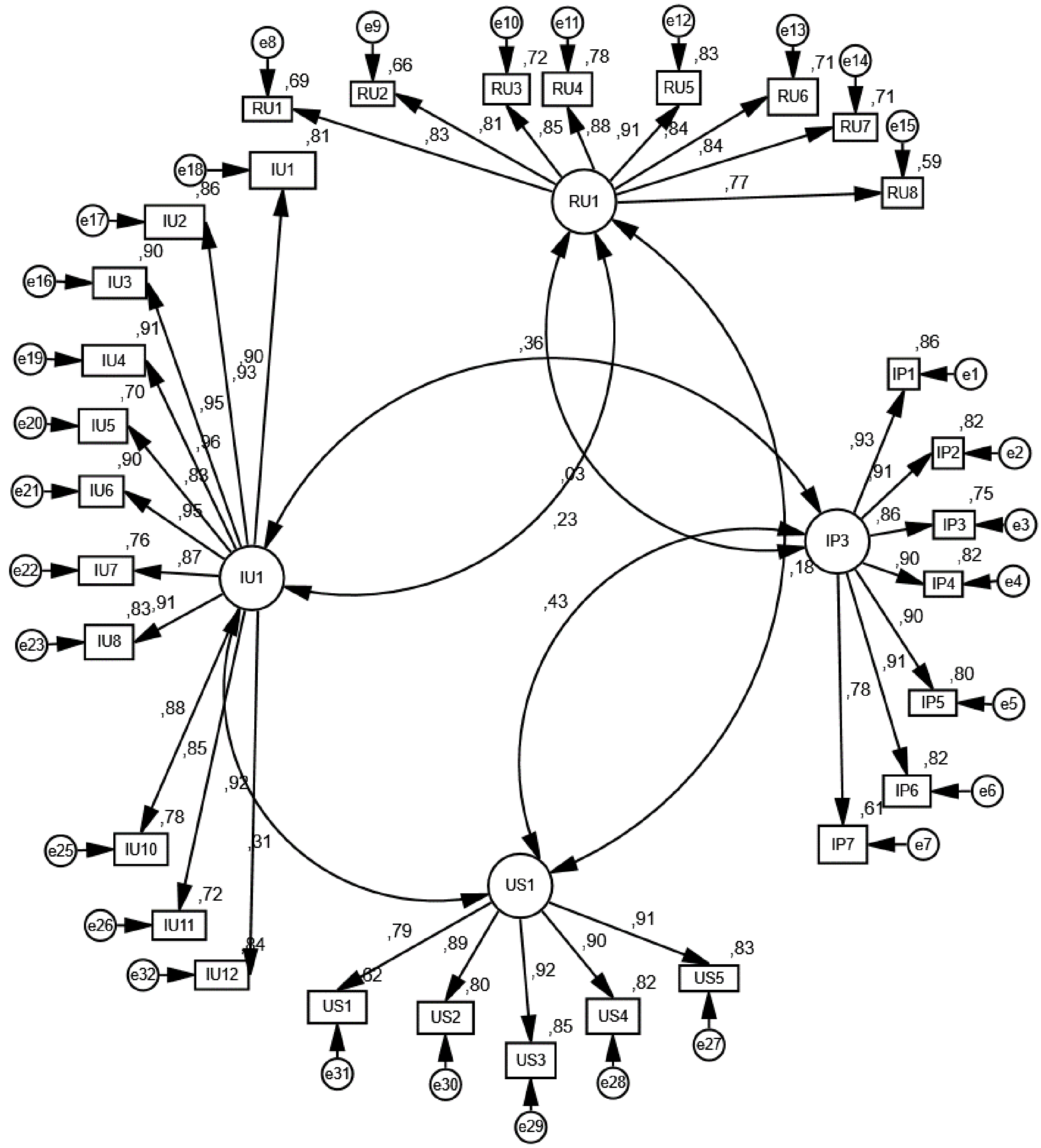
Figure 26 Initial CFA Measurement Model 2 (M_2 examines the effects of RU2, IU2 and US2 on IP3)



7.2.1.3 CFA model 3 results

Figure 27 indicates the results of the CFA being tested for M3 (routine use W_1, innovative use W_1, user satisfaction W_1 and individual performance W_3). The X^2 / DF was found to be high, which indicates that the data does not fit the model well. The M3 X^2 / DF on the CFA model is 5 which is greater than 3, this indicates that there is still room for improving the model. The M3 indicates the initial indices as follows (GFI= 0.614; NFI=0.740; CFI=0.872; IFI=0.874; RMSEA=0.11; P<0.001; DF=428; TLI=0.861 and RFI=0.717). The validity of the CFA model indicates that some model fit indices were not satisfactory. However, the main objective of the CFA model was to check if all the items of the scale are loading on the model. The CFA test was conducted to confirm construct validity and factor loadings (Serrano Archimi et al., 2018). The factor loadings of M2 range between 0.768 to 0.956 (Figure 27), which is above the prescribed threshold of 0.50. M_3 examines the effects of RU1, IU1 and US1 on IP3).

Figure 27 Initial CFA Measurement Model 3 (M3 examines the effects of RU2, IU2 and US2 on IP3)



Therefore, the validity of the three CFA models indicate that some model fit indices were not satisfactory. However, the main objective of the CFA model was to check if all the items of the scale are loading on the model. The CFA test was conducted to confirm construct validity and factor loadings (Serrano Archimi et al., 2018). It was not meant to test the hypotheses among the constructs. The results indicate that all the items are loading appropriately and in line with theory. The factor loadings of all three models range between 0.692 to 0.956, which is above the prescribed threshold of 0.50. The next section tests the hypothesised models.

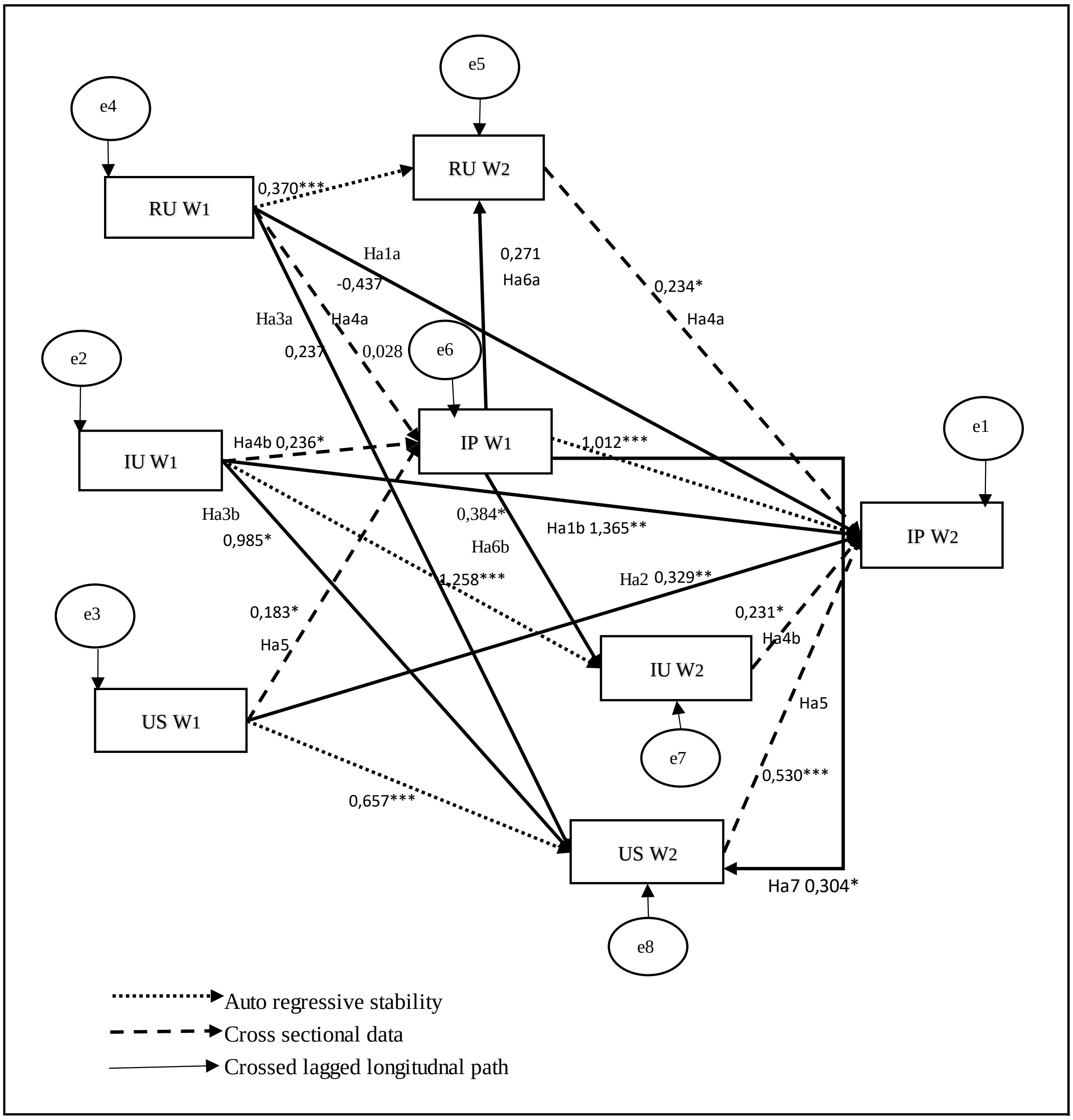
7.2.2 Model one Testing of Causal Relationship Between Use W1, User satisfaction W1 and Individual Performance W2

The above presented results indicate that reliability, convergent validity, and discriminant validity have been confirmed by both EFA and CFA techniques. The next stage is to test the hypothesised causal relationships between the exogenous and endogenous latent constructs (refer to Figure 8), which is done through the test of the structural model. In this stage, the relationships between independent and dependent variables are specified. The causal relationships between independent and dependent variable are indicated through a one head arrow. In this study, only "free" pathways are modelled for hypothesised causal relationships between the variables that are being tested. The free pathways are left free to vary, there are no fixed pathways, as dictated by previous studies (Serrano Archimi et al., 2018; Hair et al., 2010; Sangthong, 2020) in this model. The sample being used for model testing is the 59 responses that were matched from W_1, W_2 and W_3 only.

7.2.2.1 Original structural model (M1)

The test of the originally hypothesised (M_1) model is illustrated in Figure 28. The model (M_1) measures the cross-lagged effects from W_1 (routine use, innovative use, user satisfaction) to W_2 individual performance of the 59 matched responses, where W_2 data was collected 12 weeks after W_1. The Chi-square (X^2) was found to be high and the ratio of X^2 / DF=5 is higher than the recommended value of less than 3, which indicates that the data does not fit the model well. This test may however reject the hypotheses unnecessarily (Hair et al., 2010) as even small differences between the observed model and the good model fit might be found to be significant. The fit indices were as follows: [GFI=0.798; NFI=0.959; CFI=0.986; IFI=0.965; RMSEA=0.102; TLI=0.886; RFI=0.836] indicating some bad fit on other indices of the model (M_1). There was thus a need for model (M_1) improvement so that a better model fit could be achieved.

Figure 28 Original Cross-lagged Model (M_1) Testing



7.2.2.2 Final cross-lagged model (M1) testing

After modifications, the results of final cross-lagged model (M_1) are presented in Figure 29. The model (M_1) measures the cross-lagged effects of routine use (W_1), innovative use (W_1), user satisfaction (W_1) on individual performance (W_2).

The final model indicates the P>0.050 which is non-significant, compare to the default model, however the X^2/DF=4 is still somewhat higher than the recommended value of less than 3. Based on the second run of the model, the results of model fit had improved as presented below in Table 50. The fit indices were as follows: [GFI=0.967; NFI=0.964; CFI=1.000; IFI=1.000;

RMSEA=0.000; DF=6; TLI=1.000; RFI=0.845] indicating a good model fit in most of the indices.

Table 50 Goodness of Fit Indices for M_1

Fit Index	Recommended Value	CFA Results	Original Structural Model	Final Structural Model
Goodness-of-fit (GFI)	Less than 0.80 (No fit) Between [0.80-0.90] (acceptable) Above 0.90 (Perfect fit)	0.600	0.798	0.967
Normed fit index (NFI)	Less than .80 (bad) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.732	0.959	0.964
Comparative fit index (CFI)	Less than 0.90 (bad) Above 0.90 (good)	0.863	0.986	1.000
Incremental fit index (IFI)	Less than 0.90 (bad) Above 0.90 (good)	0.865	0.965	1.000
Root mean square error of approximation (RMSEA)	Less than 0.05 (good) Between [0.06-1] (acceptable) Above 1 (bad)	0.113	0.102	0.000
Chi-square ($\chi 2$ /DF)	Less than 3 (good) Between [3-5] (acceptable) Above 5 (bad)	6	5	4
Tucker-Lewis Index (TLI)	Less than 0.80 (bad) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.851	0.886	1.000
Relative Fit Index (RFI)	Less than 0.80 (bad) Between [.80-.90] (acceptable) Above .90 (good)	0.709	0.836	0.845

Model improvement steps taken

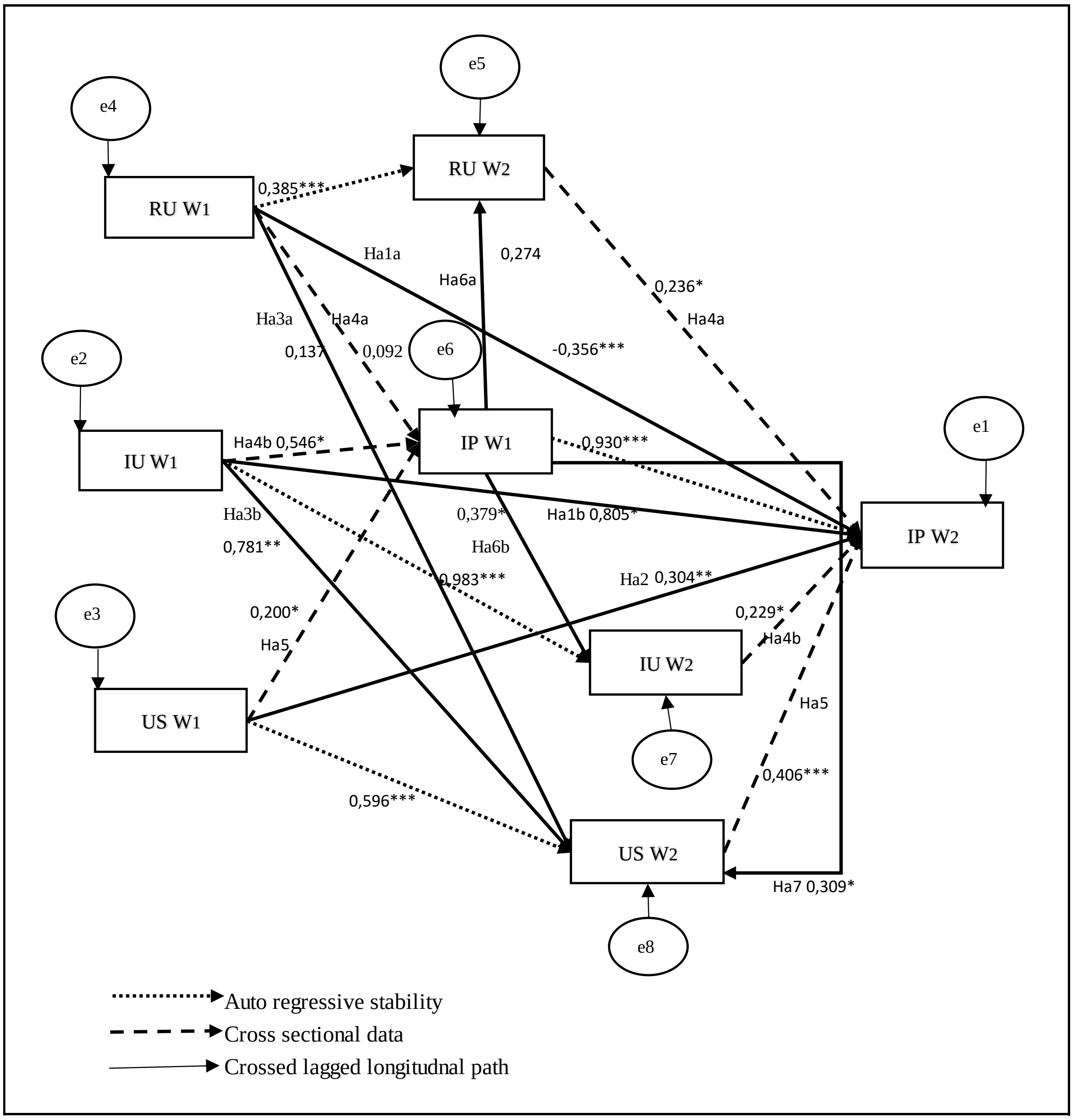
To achieve the above model fit, the modifications presented in Table 51 were undertaken, based on examination of the AMOS output. Specifically, errors with high covariance were covaried, which is considered acceptable if they will not compromise the theoretical model being tested (Fan and Sivo, 2005).

Table 51 Modification Indices M₁

Covariances	M.I.	Par Change
e2<-->e3	4.106	0.228
e3<-->e4	5.247	0.395

The results after this final improvement are illustrated next.

Figure 29 Final Cross-lagged Model (M_1) Test Results (indicators to latent variables and covariances are not illustrated to improve presentations**)**



The final indices suggest it was acceptable to proceed with examination of the hypothesised relationships within the model (M_1). Table 52 indicates the path coefficients of the hypothesised relationships within the proposed research model.

Table 52 The Cross-lagged Results of Hypothesised Model (M_1)

Hypothesis		Estimate	S.E.	C.R.	P	Supported
Ha1a	IP2<---RU1	-0.356	0.104	-3.416	0.000	No (negative relationship)
Ha1b	IP2<---IU1	0.805	0.330	2.438	0.015	Yes
Ha2	IP2<---US1	0.304	0.109	2.799	0.005	Yes
Ha3a	US2<---RU1	0.137	0.139	0.984	0.325	No
Ha3b	US2<---IU1	0.781	0.228	3.425	0.000	Yes
Ha4a cross-sectional data	IP1<---RU1	0.092	0.079	1.163	0.245	No
	IP2<---RU2	0.236	0.105	2.235	0.025	Yes
Ha4b cross-sectional path	IP1<---IU1	0.546	0.244	2.239	0.025	Yes
	IP2<---IU2	0.229	0.108	2.128	0.033	Yes
Ha5 cross-sectional path	IP1<---US1	0.200	0.080	2.482	0.013	Yes
	IP2<---US2	0.406	0.092	4.398	0.000	Yes
Ha6a	RU2<---IP1	0.274	0.162	1.690	0.092	No
Ha6b	IU2<---IP1	0.379	0.168	2.257	0.024	Yes
Ha7	US2<---IP1	0.309	0.165	1.873	0.049	Yes
US1=User satisfaction Wave 1 US2=User satisfaction Wave 2 RU1=Routine use Wave 1 RU2=Routine use Wave 2 IU1=Innovative use Wave 1 IU2=Innovative use Wave 2 IP1=Individual performance Wave 1 IP2=Individual performance Wave 2						

Table 53 R-squared Results Model (M_1)

Variables	Estimate
IP1	0.147
US2	0.231
RU2	0.202
IU2	0.320
IP2	0.615

As presented in Table 52, 10 out of 15 hypotheses were directly supported on the model being tested. The cross-lagged model (M_1) measures the effects of innovative use W_1, routine use W_1 and use satisfaction W_1 on individual performance W_2. The model also includes the impact of use (innovative and routine) W_1 on user satisfaction W_2. In addition, the effect of individual performance W_1 on use (innovative and routine) W_2 was also tested. ***Although the cross-sectional paths were modelled, the model (M_1) interpretation is focused on the cross-lagged longitudinal paths as the cross-sectional data was analysed in Chapter*** 6. The model explains

61.5% of IP at time 2 with IU, and US at time 1 significant positive factors, which is consistent with the DeLone and McLean model. The effect of RU at time 1 on performance at time 2 is negative, which is consistent with this study's hypothesis that IU is more important than RU to performance.

Figure 29 indicates that routine use at time 1 has a negative relationship on individual performance at time 2 ($P<0.001$). The hypothesis Ha1a has been rejected. This finding supports the view that innovative use of the BI system is better than routine use in improving the individual performance when comparing W_1 against W_2. Innovative use of the BI system at W_1 has a significant influence on individual performance at W_2 ($P<0.05$). This supports the need to understand the effects that the type of use may have on individual performance over time. Thus, hypothesis Ha1b has been supported. User satisfaction of the BI system at W_1 has a significant influence of individual performance at time 2 ($P<0.01$). Therefore, hypothesis Ha2 has been accepted. Individuals who are likely to attribute improvements in their performance to BI at a later stage (W_2) are those who were satisfied by the BI system at the earlier stages of use (W_1). Routine use at time 1 has no significant influence on user satisfaction at time 2 ($P>0.05$). However, innovative use at time 1 has a significant influence on user satisfaction at time 2 ($P<0.001$). Therefore, hypothesis Ha3a was rejected while Ha3b has been supported. These findings support the view that innovative use at time 1 is better than routine use at time 1 in improving use satisfaction at time 2. Individual performance at time 1 has no significant influence on routine use at time 2 ($P>0.05$). While individual performance at time 1 has a significant influence on innovative use at time 2 ($P<0.05$). Therefore, hypothesis Ha6a was rejected while Ha6b was accepted. Individuals who are likely to use innovative features of the BI systems at a later stage are those who believed it improved their performance at an early stage of BI system use. Individual performance at time 1 ($P<0.050$) also has a significant influence on user satisfaction at time 2. Therefore, hypothesis Ha7 has been accepted. This means that improvement in performance at time 1 increased the user satisfaction at time 2. Finally, the cross-sectional path also indicates that innovative use has a stronger influence on individual performance than routine use at time 1 and very similar effects at time 2. In addition, user satisfaction at time 1 and 2 has a significant influence on individual performance at time 1 and 2, but a stronger association between the two at time 2.

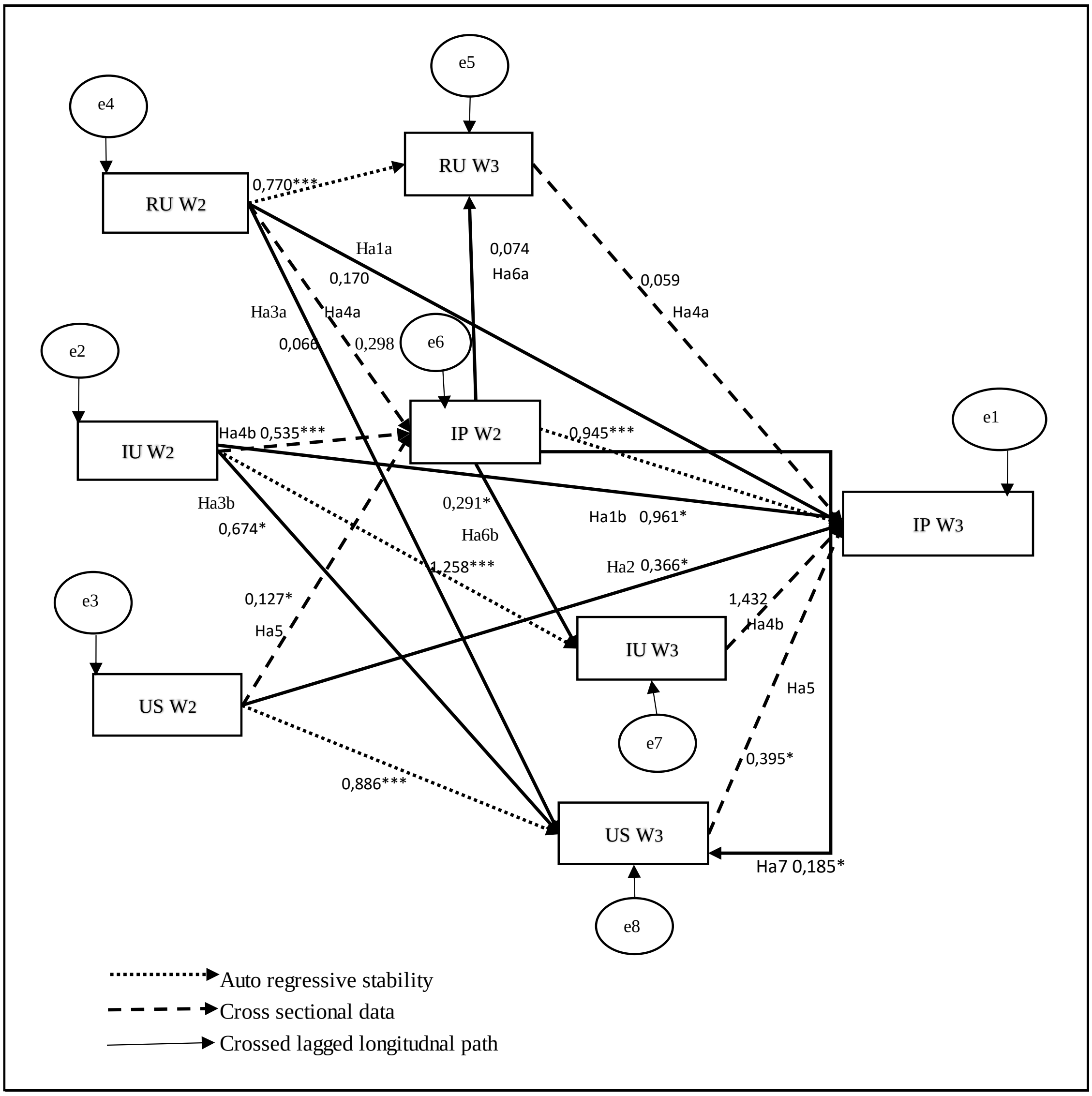
7.2.2.3 Model two testing of causal relationship between use W2, user satisfaction W2 and individual performance W3

Next, the structural model (M_2) was tested. The sample being used remains the 59 responses that were matched from W_1, W_2 and W_3. This model (M_2) focuses on the effects from W_2 to W_3, where W_3 data was collected 16 weeks after W_2.

7.2.2.4 Original structural model (M2)

The test of the originally hypothesised model (M_2) is illustrated in Figure 30. The model (M_2) measures the cross-lagged effects from W_2 (routine use, innovative use, user satisfaction) to W_3 individual performance. The Chi-square (X^2) was found to be high, which indicates that the data does not fit the model well and X^2 / DF=6 was higher than the recommended value of less than 3. The fit indices were as follows: [GFI=0.967; NFI=0.974; CFI=0.989; IFI=0.990; RMSEA=0.097; TLI=0.951; RFI=0.881] indicating a bad fit on these other indices of the model (M_2). There was a need for model (M_2) improvement.

Figure 30 Original Structural Model 2 Test Results



7.2.2.5 Final cross-lagged model (M2) testing

The results of final cross-lagged model (M_2) are presented in Figure 31. The final model after modifications indicates the P>0.050 which is non-significant, compare to the default model, however the X^2 / DF=3 is within the recommended value of less than 3. Based on the second run of the model, the results of model fit improved as presented below in Table 54. The fit indices were as follows: [GFI=0.972; NFI=0.979; CFI=0.997; IFI=0.997; RMSEA=0.046; DF=6; TLI=0.989; RFI=0.916] indicating a good model fit in most of the indices. Table 54 indicates the goodness of fit indices.

Table 54 Goodness of Fit Indices for M_2

Fit Index	Recommended Value	CFA Results	Original Structural Model	Final Structural Model
Goodness-of-fit (GFI)	Less than 0.80 (No fit) Between [0.80-0.90] (acceptable) Above 0.90 (Perfect fit)	0.565	0.967	0.972
Normed fit index (NFI)	Less than 0.80 (bad) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.702	0.974	0.979
Comparative fit index (CFI)	Less than 0.90 (bad) Above 0.90 (good)	0.829	0.989	0.997
Incremental fit index (IFI)	Less than 0.90 (bad) Above 0.90 (good)	0.832	0.990	0.997
Root mean square error of approximation (RMSEA)	Less than 0.05 (good) Between [0.06-1] (acceptable) Above 1 (bad)	0.126	0.097	0.046
Chi-square ($\chi 2$ /DF)	Less than 3 (good) Between [3-5] (acceptable) Above 5 (bad)	6	6	3
Tucker-Lewis Index (TLI)	Less than 0.80 (bad) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.815	0.951	0.989
Relative Fit Index (RFI)	Less than 0.80 (bad) Between [.80-.90] (acceptable) Above .90 (good)	0.678	0.881	0.916

Model improvement steps taken

To achieve this improved model fit, the following improvements were undertaken. These improvements were identified by examining the AMOS output.

Table 55 Modification Indices

Covariances	M.I.	Par Change
e2<-->e4	5.266	0.485

The model results are depicted in Figure 31.

Figure 31 Final Cross-lagged Model (M_2) Test Results (indicators to latent variables and covariances are not illustrated to improve presentations**)**

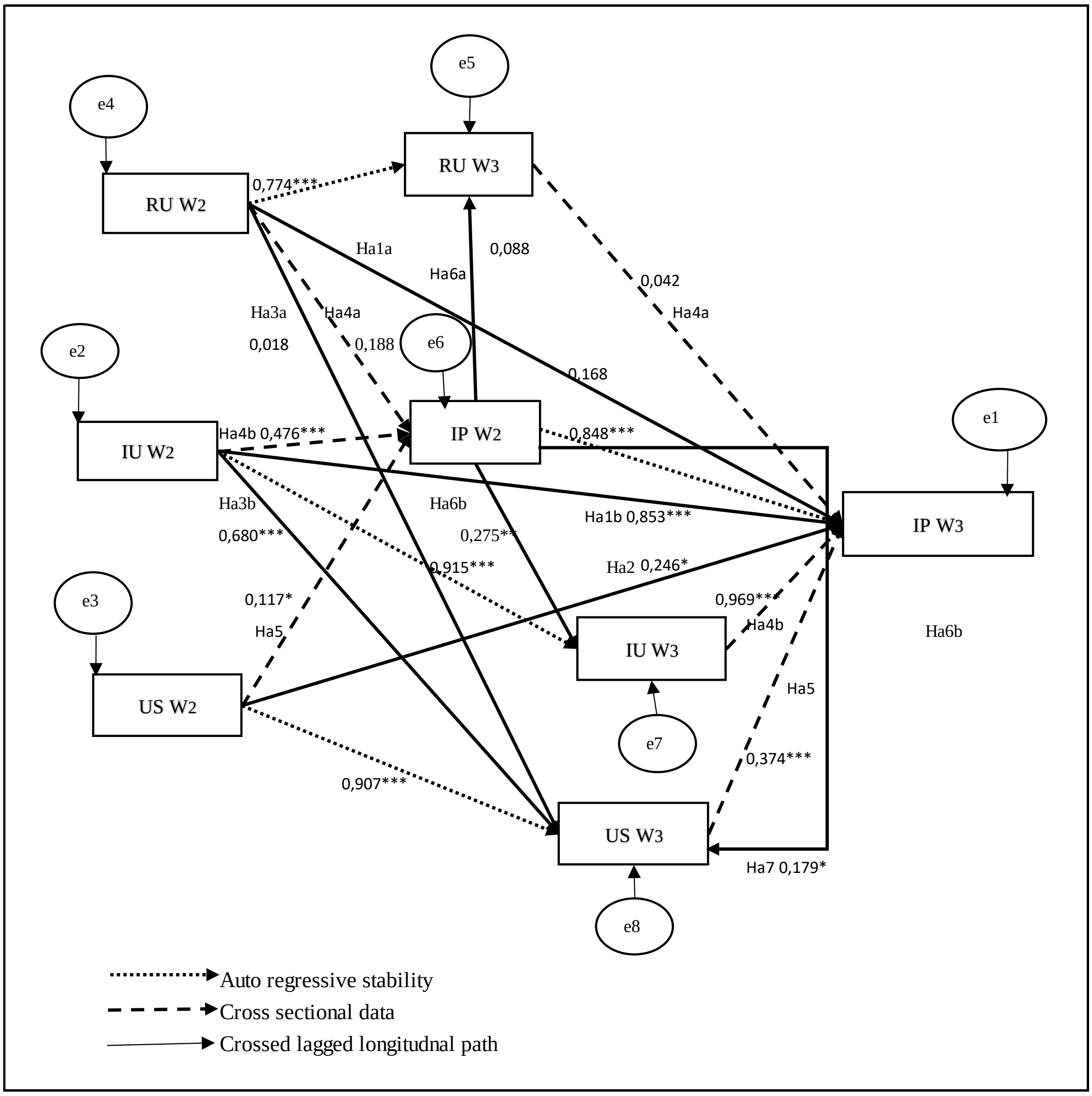


Table 56 The Cross-lagged Results of Hypothesised Model (M_2)

Hypothesis		**Estimate**	**S.E.**	**C.R.**	**P**	**Supported**
Ha1a	IP3<---RU2	0.168	0.123	1.366	0.461	No
Ha1b	IP3<---IU2	0.843	0.222	3.797	0.000	Yes
Ha2	IP3<---US2	0.246	0.118	2.090	0.037	Yes
Ha3a	US3<---RU2	0.018	0.103	0.177	0.859	No
Ha3b	US3<---IU2	0.680	0.167	4.072	0.000	Yes
Ha4a cross-sectional data	IP2<---RU2	0.188	0.138	1.368	0.171	No
	IP3<---RU3	0.042	0.118	0.360	0.719	No
Ha4b cross-sectional path	IP2<---IU2	0.476	0.147	3.230	0.001	Yes
	IP3<---IU3	0.969	0.225	4.307	0.000	Yes
Ha5 cross-sectional path	IP2<---US2	0.117	0.055	2.127	0.031	Yes
	IP3<---US3	0.374	0.109	3.431	0.000	Yes

Hypothesis		Estimate	S.E.	C.R.	P	Supported
Ha6a	RU3<---IP2	0.088	0.071	1.242	0.214	No
Ha6b	IU3<---IP2	0.275	0.097	2.835	0.007	Yes
Ha7	US3<---IP2	0.179	0.083	2.157	0.026	Yes
US2=User satisfaction Wave 2 US3=User satisfaction Wave 3 RU2=Routine use Wave 2 RU3=Routine use Wave 3 IU2=Innovative use Wave 2 IU3=Innovative use Wave 3 IP2=Individual performance Wave 2 IP3=Individual performance Wave 3						

Table 57 R-squared Results Model (M_2)

Variables	Estimate
IP2	0.224
US3	0.696
RU3	0.572
IU3	0.865
IP3	0.738

As presented in Table 56, nine out of 14 hypotheses were directly supported on the model being tested. The cross-lagged model (M_2) measures the effects of innovative use at time 2, routine use at time 2 and user satisfaction at time 2 on individual performance at time 3. The model also includes the impact of use (innovative and routine) at time 2 on user satisfaction at time 3. In addition, the effect of individual performance at time 2 on user satisfaction at time 3 was also tested. The model explains 73.8% of IP at time 3 with IU at time 3 and IU at time 2 the most significant factors followed by US at time 3, which is consistent with the DeLone and McLean model and this study's hypothesis that IU is more important than RU to performance.

Figure 31 indicates that routine use at time 2 has no influence of individual performance at time 3 ($P>0,05$). The hypothesis, Ha1a, has been rejected in this model. This finding supports the view that innovative use of the BI system is better than routine use in improving the individual performance when comparing time 2 against time 3. Innovative use of the BI system at time 2 has a significant influence on individual performance at time 3 ($P<0.001$). This confirms the early results from time 1 to time 2 and once again supports the need to differentiate between types of use when examining impacts on performance over time. Thus, hypothesis Ha1b has been supported. User satisfaction of the BI system at time 2 has a significant influence of individual performance at time 3 ($P<0.05$). Therefore, hypothesis Ha2 has been accepted. Individuals who are likely to improve their performance at a later stage (W_3) are those who were satisfied by the BI system at the earlier stage (W_2). Routine use at time 2 has no significant influence on user satisfaction at time 3 ($P>0.05$). However, innovative use at time 2 has a significant influence on user satisfaction at time 3 ($P<0.001$). Therefore, hypothesis Ha3a was rejected while Ha3b has been supported. These findings support the view that innovative use at time 2 is better than routine use at time 2 in improving use satisfaction at time 3.

Individual performance at time 2 has no significant influence on routine use at time 3 ($P>0.05$) while individual performance at time 2 has a significant influence on innovative use at time 3 ($P<0.05$). Therefore, hypothesis Ha6a was rejected while Ha6b was supported. Individuals who are likely to use innovative features of the BI systems at a later stage are those who improved their performance at an early stage of BI system use. Individual performance at time 2 ($P<0.050$) has a significant influence on user satisfaction at time 3. Therefore, hypothesis Ha7 has been accepted. This means that improvement in performance at time 2 increase the user satisfaction at time 3, which confirms the reciprocity between user satisfaction and user performance as theorised by the D&M model.

Finally, the cross-sectional path also indicates that innovative use has a stronger influence on individual performance than routine use. In addition, user satisfaction at time 2 and 3 has a significant influence on individual performance at time 2 and 3.

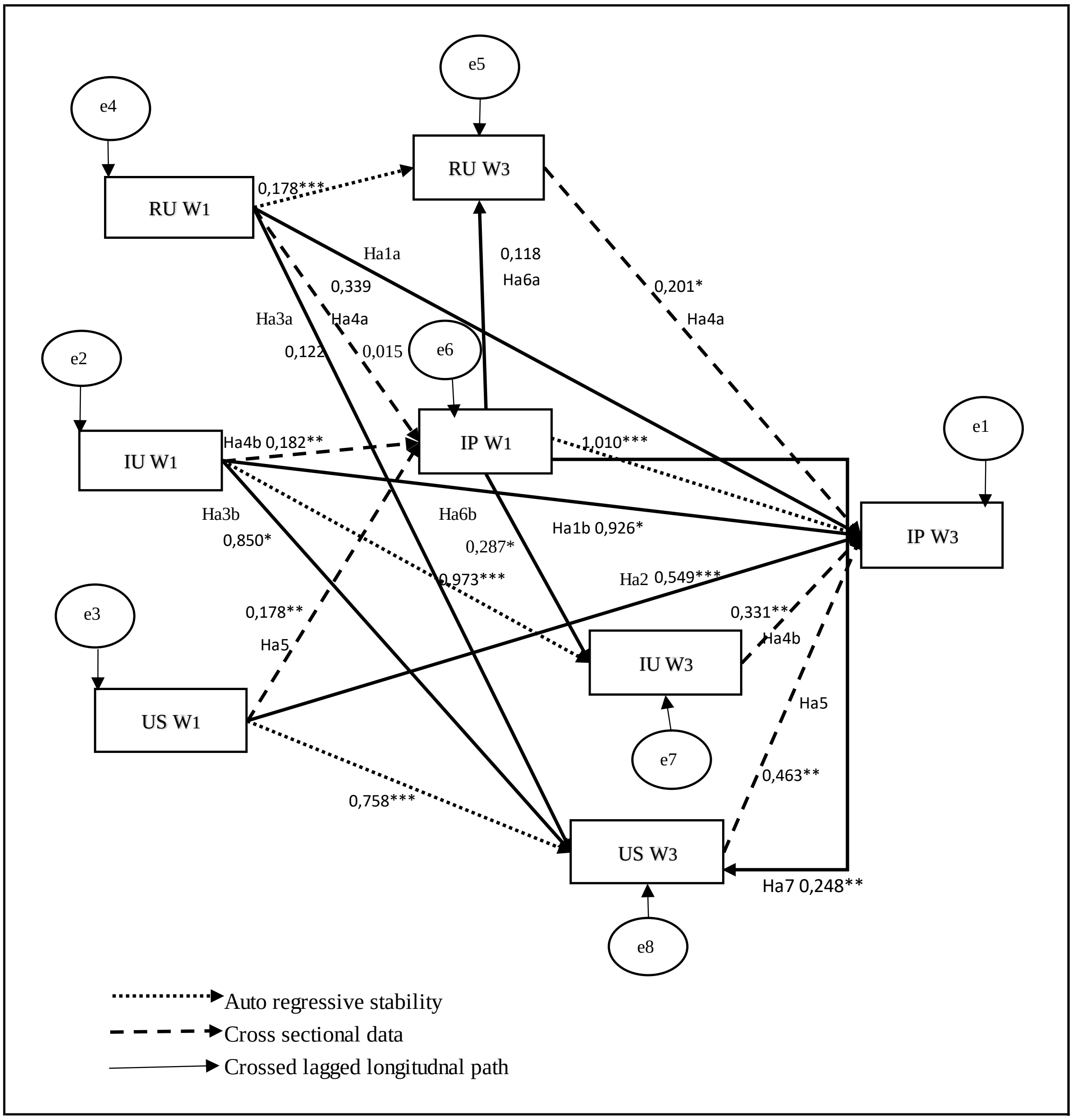
7.2.2.6 Model three testing of causal relationship between use W1, user satisfaction W1 and individual performance W3

Finally, the structural model (M_3) was tested. Although the tests of M_1 and M_2 have already established the cross-lagged effects between use, user satisfaction and performance, M_3 explores the longitudinal effects between time 1 and time 3, with W_3 data collected 28 weeks after W_1, to determine if a similar pattern of cross-lagged effects is observed. The sample being used remains the 59 responses matched across the waves.

7.2.2.7 Original structural model (M3)

The test of the originally hypothesised model (M_3) is illustrated in Figure 32. The model (M_3) measures the cross-lagged effects from W_1 (routine use, innovative use, user satisfaction) to W_3 individual performance. The Chi-square (X^2) was found to be high and the X^2 / DF=4 which is higher than the recommended value of less than 3, indicates that the data did not fit the model well. The fit indices were as follows: [GFI=0.972; NFI=0.942; CFI=0.981; IFI=0.984; RMSEA=0.074; TLI=0.910; RFI=0.729]. There was a need for model (M_3) improvement along similar lines to those reported above in tests of M_1 and M_2.

Figure 32 Original Measurement Model 3 Test Results



7.2.2.8 Final cross-lagged model (M3) testing

The results of final cross-lagged model (M_3) are presented in Figure 33. The model (M_3) measures the cross-lagged effects of routine use (W_2), innovative use (W_2), user satisfaction (W_2) on individual performance (W_3).

The final model indicates the P>0.050 which is non-significant, compare to the default model, with the X^2 / DF=2 is acceptable as it is within the recommended value of less than three. Nonetheless, the results of model fit had improved as presented below in Table 58. The fit indices are as follows: [GFI=0.983; NFI=0.972; CFI=0.988; DF=4; IFI=0.986;

RMSEA=0.058; TLI=0.932; RFI=0.846] indicating a good model fit in most of the indices. Table 58 indicates the goodness of fits indices.

Table 58 Goodness of Fit Indices for M_3

Fit Index	**Recommended Value**	**CFA Results**	**Original Structural Model**	**Final Structural Model**
Goodness-of-fit (GFI)	Less than 0.80 (No fit) Between [0.80-0.90] (acceptable) Above 0.90 (Perfect fit)	0.614	0.972	0.983
Normed fit index (NFI)	Less than .80 (bad) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.740	0.942	0.972
Comparative fit index (CFI)	Less than 0.90 (bad) Above 0.90 (good)	0.872	0.981	0.988
Incremental fit index (IFI)	Less than 0.90 (bad) Above 0.90 (good)	0.874	0.984	0.986
Root mean square error of approximation (RMSEA)	Less than 0.05 (good) Between [0.06-1] (acceptable) Above 1 (bad)	0.110	0.074	0.058
Chi-square ($\chi 2$ /DF)	Less than 3 (good) Between [3-5] (acceptable) Above 5 (bad)	5	4	2
Tucker-Lewis Index (TLI)	Less than 0.80 (bad) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.861	0.910	0.932
Relative Fit Index (RFI)	Less than 0.80 (bad) Between [.80-.90] (acceptable) Above .90 (good)	0.717	0.729	0.846

Model improvement steps taken

To achieve the improved model fit, the following improvements were undertaken.

Table 59 Modification Indices

Covariances	**M.I.**	**Par Change**
e2<-->e3	5.803	0.357
e2<-->e4	6.451	0.484

The results after this final improvement are illustrated next.

Figure 33 Final Cross-lagged Model (M_3) Test Results (indicators to latent variables and covariances are not illustrated to improve presentations)

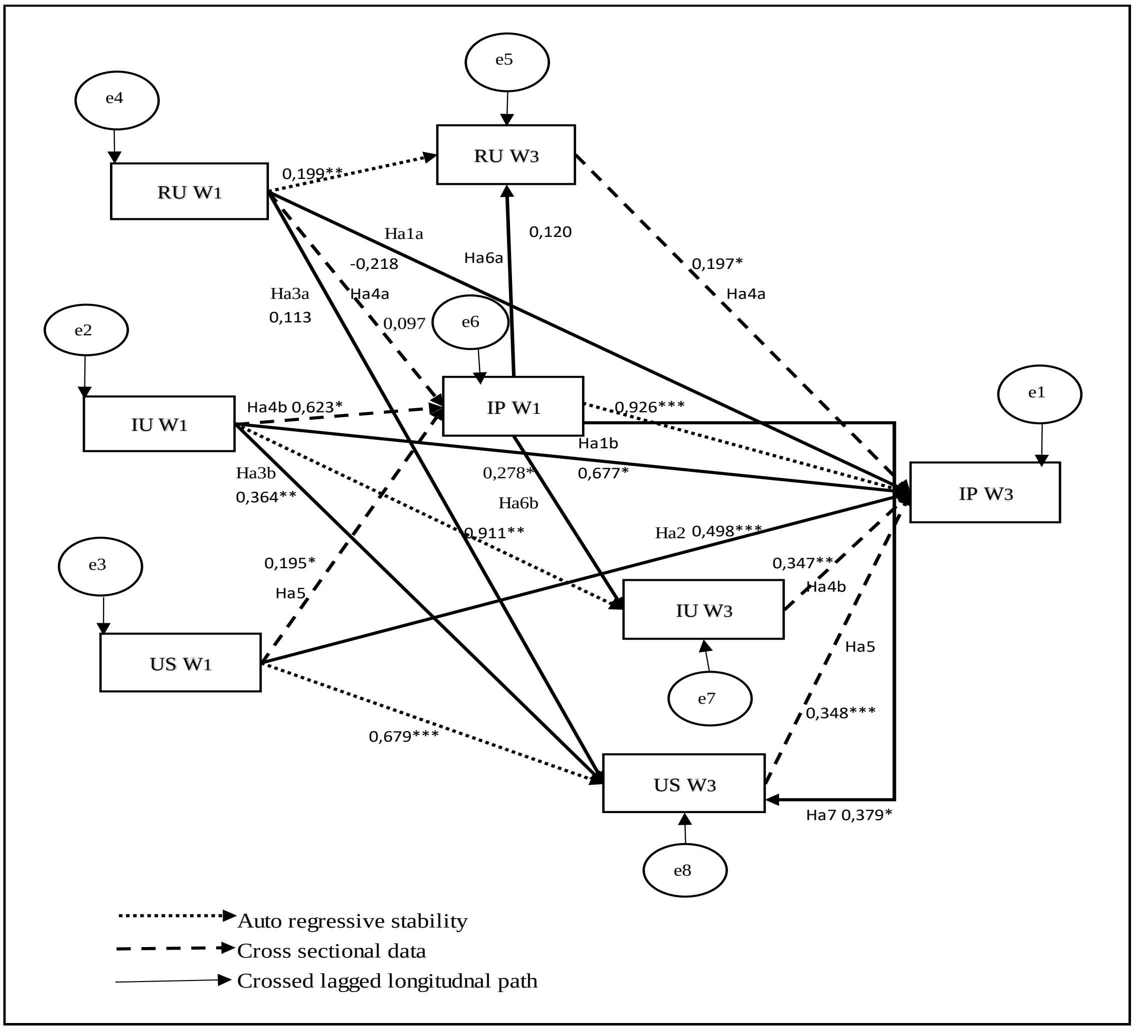


Table 60 The Results of Hypothesised Model 3

Hypothesis		Estimate	S.E.	C.R.	P	Supported
Ha1a	IP3<---RU1	-0.218	0.096	-2.281	0.023	Not supported, negative
Ha1b	IP3<---IU1	0.677	0.324	2.091	0.036	Yes
Ha2	IP3<---US1	0.498	0.115	4.326	0.000	Yes
Ha3a	US3<---RU1	0.113	0.123	0.919	0.320	No
Ha3b	US3<---IU1	0.364	0.148	2.459	0.01	Yes
Ha4a	IP1<---RU1	0.097	0.079	1.232	0.218	No
	IP3<---RU3	0.197	0.095	2.074	0.039	Yes
Ha4b	IP1<---IU1	0.623	0.258	2.414	0.016	Yes
	IP3<---IU3	0.347	0.109	3.175	0.001	Yes
Ha5	IP1<---US1	0.195	0.080	2.450	0.014	Yes
	IP3<---US3	0.348	0.097	3.584	0.000	Yes
Ha6a	RU3<---IP1	0.120	0.176	0.684	0.494	No
Ha6b	IU3<---IP1	0.278	0.134	2.075	0.038	Yes
Ha7	US3<---IP1	0.379	0.185	2.049	0.042	Yes
US1=User satisfaction Wave 1 US3=User satisfaction Wave 3 RU1=Routine use Wave 1 RU3=Routine use Wave 3 IU1=Innovative use Wave 1 IU3=Innovative use Wave 3 IP1=Individual performance Wave 1 IP3=Individual performance Wave 3						

Table 61 R-squared Results Model (M_3)

Variables	Estimate
IP1	0.153
US3	0.411
RU3	0.051
IU3	0.154
IP3	0.620

As presented in Table 60, 10 out of 14 hypotheses were directly supported on the model being tested. The model explains 62% of IP at time 3 with IU at time 1 the most significant factor followed by US at time 1, which is consistent with the DeLone and McLean model and confirmed across time waves. The effect of routine use at time 1 is negative, which adds further support for this study's hypothesis that IU is more important than RU to performance.

Figure 33 indicates that routine use at time 1 has a negative influence of individual performance at time 3 (P<0.05). The hypothesis, Ha1a, has been rejected. This finding supports the view that innovative use of the BI system is better than routine use in improving the individual performance when comparing time 1 against time 3. Innovative use of the BI system at time 1 has a significant influence on individual performance at time 3 (P<0.050). This supports the need to understand the effects that the type of use may have on individual performance over time. The early intention to use BI system is affected more by innovative use of the BI system as compared to the routine use of the BI system when measuring improvement of individual performance at the later stage. Thus, hypothesis Ha1b has been supported. User satisfaction of the BI system at time 1 ($P<0.001$) has a significant influence of individual performance at time 3. Therefore, hypothesis Ha2 has been accepted. Individuals who are likely to improve their performance at a later stage (W_3) are those who were satisfied by the BI system at the earlier stage (W_1). Routine use at time 1 ($P>0.05$) has no significant influence on user satisfaction at time 3. However, innovative use at time 1 ($P<0.01$) has a significant influence on user satisfaction at time 3. Therefore, hypothesis Ha3a was rejected while Ha3b has been supported. These findings support the view that innovative use at time 1 is better than routine use at time 1 in improving use satisfaction at time 3.

Individual performance at time 1 has no significant influence on routine use at time 3 ($P>0.05$), while individual performance at time 1 has a significant influence on innovative use at time 3 ($P<0.05$). Therefore, hypothesis Ha6a was rejected while Ha6b was supported. Individuals who are likely to use innovative features of the BI systems at a later stage are those who improved their performance at an early stage of BI system use. Individual performance at time 1 ($P<0.050$) has a significant influence on user satisfaction at time 3. Therefore, hypothesis Ha7 has been accepted. This means that improvement in performance at time 1 increases the user satisfaction at time 3. Finally, the cross-sectional path also indicates that innovative use has a stronger influence on individual performance than routine use. In addition, user satisfaction at times 1 and 3 has a significant influence on individual performance at times 1 and 3.

7.2.2.9 Summary of findings

The three cross-lagged causal models were tested above over the three waves. This study was underpinned by the D&M IS success model. The factors influencing the innovative use of the system were confirmed in Chapter 6 as system quality, data quality, information quality and service quality. In this Chapter, the causal relationships between use, user satisfaction and individual performance were tested using cross-lagged SEM models in AMOS.

The results of these tests support the view that innovative use of the BI system is better than routine use in improving the individual performance in both the three cross-lagged models (M_1, M_2 and M_3). In addition, early stage of user satisfaction was confirmed to have an influence on later stage improvement in individual performance. Furthermore, the reciprocal relationship between early-stage individual performance and later stage use was supported. Early-stage individual performance has a stronger impact on later stage innovative use as compared to later stage routine use of the BI system. Finally, early stage of individual performance has a significant impact on later stage use satisfaction. Therefore, this study's IS success model for BI was confirmed through a longitudinal data over three waves.

The effects of cross-lagged models are summarised below:

BI success factor (Path)	Results
Routine use to individual performance	This effect was not supported by longitudinal data across the three-time waves.
Innovative use to individual performance	This effect was supported by longitudinal data across the three-time waves and, as expected, contributed more compared to routine use.
User satisfaction to individual performance	This effect was supported by longitudinal data across the three-time waves.
Routine use to user satisfaction	This effect was not supported by longitudinal data across the three-time waves.
Innovative use to user satisfaction	This effect was supported by longitudinal data across the three-time waves.
Individual performance to routine use	This effect was not supported by longitudinal data across the three-time waves.
Individual performance to innovative use	This effect was supported by longitudinal data across the three-time waves.
Individual performance to user satisfaction	This effect was supported by longitudinal data across the three-time waves.

The hypotheses of various models are summarised below with its path coefficients:

Hypothesis		**Path coefficients**			**Supported**
		M_1	**M_2**	**M_3**	
Ha1a	IP<---RU	-0.356	0.168	-0.218	No
Ha1b	IP<---IU	0.805	0.843	0.677	Yes
Ha2	IP<---US	0.304	0.246	0.498	Yes
Ha3a	US<---RU	0.137	0.018	0.113	No

Hypothesis		Path coefficients			Supported
		M_1	M_2	M_3	
Ha3b	US<---IU	0.781	0.680	0.364	Yes
Ha6a	RU<---IP	0.274	0.088	0.120	No
Ha6b	IU<---IP	0.379	0.275	0.278	Yes
Ha7	US<---IP	0.309	0.179	0.379	Yes

The R-squared results on the dependent constructs of the three models are summarised below:

Variables	R-squared		
	M_1	M_2	M_3
IP	0.147	0.224	0.153
US	0.231	0.696	0.411
RU	0.202	0.572	0.051
IU	0.320	0.865	0.154
IP	0.615	0.738	0.620

7.3 Discussion

Causality is the basis of good theory (Gregor, 2006). The causality phenomenon has been a topic of intense deliberations in various disciplines. Cross-sectional data cannot be used to establish causal relationships, hence the need for a longitudinal time wave study. The use of a longitudinal study is considered a better option in examining the causal relationships in a model. The focus on the longitudinal data emanates from the nature of cross-sectional data that provide informative data, however they might be misleading due to the common method bias element (Awang et al., 2015; Son and Taamouti, 2019). The longitudinal study, as applied in this study and to the topic of BI use, is still emerging and is unprecedented in the literature. The concept of use can be a dynamic process that can evolve over time, and it is always a challenge to decide on where to position the cross-sectional effort. In a longitudinal study, it is easier to understand the evolution and dynamic nature of information system use (Gregor, 2006; Grover, 2019).

The purpose of this chapter was to understand the causal relationships amongst routine use, innovative use, user satisfaction and individual performance over the three waves (W_1, W_2 and W_3). In establishing the causal relationships, three models were tested (M_1, M_2 and M_3) (Figure 29; 31 and 33). More specifically, to address RO2, which is to examine the impact of innovative use of BI systems on the individual-level performance of management accountants, the Chapter examined the impact of innovative use of BI systems on the individual-level performance of management accountants over the three waves. To do so, a BI system success model was developed and empirically tested. The DeLone and McLean (D&M) IS Success Model provided the initial underpinning for the model's development. Data was collected from individual management accountants from the private and public companies in South Africa over three waves. The study extended the conceptualisation of system usage to include both routine and innovative use dimensions and obtained the South African BI system user's perspective on BI system success factors through a large sample survey over the three waves. The AMOS test results for M_1, M_2 and M_3 are presented in Figure 29, 31 and 33, respectively. The results are discussed in the next section in detail.

7.3.1 Cross-lagged Type of Use

The results provided answers to the question on the impact of innovative use of BI systems on the individual-level performance of management accountants over three waves.

The effects of cross-lagged models are summarised below:

BI System Success Factor	**Model 1 (W1 to W2)**	**Model 2 (W2 to W3)**	**Model 3 (W1 to W3)**
RU to both IP and US	No	No	No
IU to both IP and US	Yes	Yes	Yes
RU=Routine use IU=Innovative use US=User satisfaction IP=Individual performance			

Within the D&M IS success model, system use has typically been conceptualised as a single unidimensional construct (Delone and McLean, 2003; Li, Hsieh and Rai, 2013). The concept of IS use as a single attribute has been widely studied as an important system attribute leading to overall IS success (Yakubu and Dasuki, 2018; Schierder and Gluchowski, 2011; Popovič et al., 2014; Ashrafi et al., 2019). Past research into IS use at an individual level of performance has focused almost exclusively on cross-sectional data without employing a cross-lagged longitudinal study design (Courtois et al., 2014; Liew, 2019), which is much better for understanding whether early-stage use has an impact on later-stage outcomes. Moreover, given that the emphasis of BI system use is on the type and intensity of the utilization of the BI solution (Dinter et al., 2011), there is a need to fully understand the ways that individuals can utilise the BI systems to improve their individual performance over time. Yet, the distinction between routine and innovative has not been fully understood in the context of BI system, and certainly not over time. Benlian (2015) conducted a longitudinal study on IS and only focused on routinisation and extent of use. Drawing on the work of Hajri et al. (2014), this study has contributed by conceptualising use as consisting of both routine use and innovative use. Understanding the routinisation and innovative use is important in determining how BI systems can lead to improvement of individual level of performance over time (Ahearne, Jelinek, and Rapp, 2005). The achievement of individual performance is dependent on how the BI system is used and the period for which it has been used.

Routine use of the system is about the use of the basic features of the BI system in performing the function (Hajri et al., 2014; Chen, 2010). If users are unable to use the advanced features of the BI system, they would normally be using the system routinely in support of their work. Routine use has no significant contribution on individual level of performance for both M_1, M_2 and M_3. This means that routine use contributes less to job productivity and performance in all three waves than innovative use of the BI system. All the cross-lagged models indicate routine use as less important than innovative use. Surprisingly, the study contradicts the work of Benlian (2015), who found that routine use contributes to improvement in performance outcomes. Instead, the findings reported here indicate routine use contributes less to individual performance and quality of decision making as compared to the innovative use of the BI system in the models (M_1[15], M_2[16] and M_3[17]). This was expected to be the case as routine means the basic use of the BI system by individual management accountants. There is an expectation that the user should start by using the routine features and at a later stage shift to innovative use. Routine features used by management accountants are drawing pre-defined existing reports, existing queries, basic analysis, use of Excel, *ad hoc* reporting and data cleansing. Because the results of the study found that both routine use and innovative use are important to performance but that innovative use has a stronger path coefficient, future research should continue to

[15] M_1 cross-lagged model that explains innovative use at time 1, routine use at time 1, user satisfaction at time 1 and individual performance at time 2.
[16] M_2 cross-lagged model that explains innovative use at time 2, routine use at time 2, user satisfaction at time 2 and individual performance at time 3
[17] M_3 cross-lagged model that explains innovative use at time 1, routine use at time 1, user satisfaction at time 1 and individual performance at time 3

distinguish between the two. Moreover, practitioners should train users on the two types of use separately and find ways to encourage more innovative use, specifically by manipulating system quality, data quality, service quality and information quality that were found to be important factors for innovative use in Chapter 6. Another opportunity for future study exists to explore different ways individuals might come to increase their innovative use by leveraging experiences after initial routine use. The use of the BI system over time may allow users to discover new innovative features and become more comfortable with innovative features of the BI system.

Innovative use is a critical element in supporting the management accountants in their job performance and quality of decision making (Chen and Cheng, 2009; Hajri et al., 2014; Chen, 2010). This study found that in all models (M_1, M_2 and M_3), innovative use of BI system improves individual performance. The cross-lagged longitudinal path in the models was shown to be strong. However, the innovative use of the BI system was found to be diminishing given the observed means across the three-time waves. This might suggest growth in innovative use has a saturation point, which is typical for self-learning behaviour (Iivari, 2005). Yet users can improve their individual performance and decision making if they continue to use advanced features of the BI system over time. The advanced features that are more likely to affect job performance and decision making over time are predictive analytics, interactive visualisation, drill down functions, dashboard reporting, self-service tools, and predictive modelling. However, it also emerged that the use of specific features for scenario planning, agile visualisation, optimisation, query construction and trends analysis were seen to be improving over time particularly in time 3. This further supports the importance of longitudinal data to evaluate the effects of using the BI system over time. The use of BI systems over time allows users to establish routines and habits of using the innovative features and this decreases the effort involved. This study found that the ability to use features of the BI system over time to achieve innovative use will affect productivity and the quality of decision making. Innovative use contributed to the improvement of job productivity and performance over the three waves. In addition, innovative use was found to improve user satisfaction. This study found that later innovative use of the system was influence by individuals who were satisfied by the BI system meeting their reporting requirements. Users are expected to engage more with the system to find new ways of using it in supporting their work (Benlian, 2015). This is a new contribution of this thesis as previous studies (Delone and McLean, 2003; Wang et al., 2007; Chen, 2010; Hou, 2012; Angelina et al., 2019) only focused on cross-sectional studies. The use of a longitudinal study can indicate patterns of innovative use over time. In this way, it is easier to learn about causes and effects of the causal relationship of innovative use and individual level performance. The coefficient path significantly improved when comparing individual performance at time 1 against individual performance at time 3. This confirms that early innovative use is important and contributes successfully to downstream individual performance and remains more important than routine use. Thus, while innovative use can improve over time, achieving innovative use early on should be a strategy when implementing BI into management accounting.

7.3.2 User Satisfaction

Within the D&M IS success model, user satisfaction is a system success factor linking the attributes of the system (e.g., system and information quality) to use and benefits. User satisfaction is regarded as an attitude that the user has of a particular information system (Wang et al., 2007). User satisfaction reflects the user's attitude toward the system that arises from the user experience of the BI system relative to the initial expectations for outcomes. The user's satisfaction has been widely studied as important to the net benefits derived from the use of the BI system (Wierder and Ossimitz, 2015; Cohen et al., 2016; Serumaga-Zake, 2017; Gaardboe et al., 2017). However, user satisfaction on post adoption of the IS has been under-studied and there remains a need to understand the patterns that might arise from user satisfaction over time. Repeated evaluation of user satisfaction over time with other major IS attributes (i.e., innovative use and performance) can help to explain more clearly how user satisfaction arises and possible implications of increasing or decreasing satisfaction for ongoing use of a BI system.

This study found that in all models (M_1, M_2 and M_3), user satisfaction with the BI system improves individual level performance over time. Management accountants appear to continue to enjoy the use of the BI system over time, which is perceived as contributing to their future productivity, effectiveness and quality of decision making. Lower levels of system use result from displeasure, frustrations and pressure that would lead to inefficiencies in system usage. Whilst high usage of the IS system results from increased satisfaction and better quality of the users' work life (Yakubu and Dasuki, 2018; Dinter, Schieder and Gluchowski, 2011). User satisfaction has been supported over time as one of the important elements of a BI system that has an influence on the improvement in individual performance.

Results obtained earlier reported that user satisfaction can be sustained over time by maintaining the system's ease of use and continuing to ensure that data is of a high quality. In addition, it was found here that innovative use improves user satisfaction over time and is more important to satisfaction than the experience of routine use. Users who use the innovative features of BI systems are found to enjoy using the system. Managing users' expectations and considering gradual use of the advanced features of technology with appropriate support can alleviate user's dissatisfaction (Courtois et al., 2014).

The results of this study are similar with those of other researchers into different types of information systems (Torkzadeh and Doll, 1999; Iivari, 2005; Petter et al., 2008), however their conclusions relied only on cross-sectional data as compared to the longitudinal data provided here in the BI context. This study has thus made an important contribution methodologically by measuring user satisfaction patterns over time. This is critical in ensuring that the users continue to use the BI system to improve their satisfaction and avoid dissatisfaction that may results in discontinuation after early-stage use. Dissatisfaction has the potential of making users despondent and reluctant to use the system, and affect individual level performance, which may defeat the purpose of implementing the BI system.

7.3.3 Individual Performance

The D&M IS success model includes net benefits of system use as the eventual outcome of an IS system's use. These benefits are considered both at the individual level and the aggregate organisational level. In this chapter, the interest is on the individual level benefit. Here, the net benefits measure the comprehensive impact of using the IS systems on the individual user of the IS system. These benefits have been regarded as the most important IS success factor by DeLone and McLean (2003). For this study, individual performance was defined as the Management Accountant's perception of the extent to which the BI system was increasing their work productivity, decision making effectiveness, performance and problem solving (Hou, 2012; Igbaria and Tan, 1997). The study found that individual level performance was associated with prior use of the advanced features of a BI system, while individual performance level was not improved through the continuous use of only the basic features of a BI system. The finding supports the work performed by Benlian (2015) who theorised that expanding the information technology features' use over time may lead to performance improving. However, the use of the same information technology features without adapting them does not guarantee improvement in performance over time (Benlian, 2015). Hence, innovative use improved BI user's individual level performance, while routine use did not. User satisfaction at all waves was also found to contribute towards the improvement of individual level performance. The role of the BI system in improving decision-making quality and speed were found to be critical indicators of the improvement in individual performance over time. This means that individuals, through their use of BI, can improve their productivity by focusing more on analysing information produced by the BI system. It is evident that management accountants should focus on using the BI system in assisting them with problem identification if they still want to continue with the improvement in their individual performance. It is important to understand how the innovative use of information technology occurs from the initial stage over subsequent periods to avoid technology failure. In addition, this study found that early-stage performance improvement contributes to later stage use and resulted in users using more innovative features of the BI system, such as predictive analytics, in supporting their work. Importantly, a user is expected to engage more with the system to find new ways of using it in supporting their work (Hajri et al., 2014). These results thus support the reciprocal causal effects between use and benefits theorised in the original D & M IS model. This supports the finding of Delone and McLean (2003) who theorised that the higher the net benefits, the more the system use. Furthermore, this study found that the net performance benefits at earlier time waves resulted in greater user satisfaction at subsequent time waves. This supports the finding of Petter et al. (2008) who stated that the higher the net benefits, the more the system would be used and improve user satisfaction. These results thus support the reciprocal causal effects between satisfaction and benefits theorised in the original D & M IS model.

This finding is an additional contribution of this thesis as previous studies drawing on the D&M IS success model have rarely examined the relationships longitudinally and have not explained the patterns of IS success relationships over time. Further, these findings provide important insights into BI use in the management accounting context. Studies of IS success have been conducted using cross-sectional data in areas such as nursing, education, and marketing environments (e.g., Cohen et al., 2016; Chen, 2010; Chen and Cheng, 2009; Isaac et al., 2017; Gaardboe et al., 2017; Angelina et al., 2019). This study adds by demonstrating D&M IS success model as relevant for understanding IS success in the management accounting context, with extensions to our understanding of routine vs innovative use and where individual management accountants represent the domain or community of users of BI systems (e.g., Benlian, 2015; Torkzadeh and Doll, 1999; Iivari, 2005). BI systems should continue to be developed for use by management accountants, and the use of advanced innovative features encouraged.

7.4 Conclusion

This chapter focused on understanding the causal relationships amongst routine use, innovative use, user satisfaction and individual performance. This was best achieved by establishing temporal precedence by collecting and analysing data over three times waves (W_1, W_2 and W_3). Wave 2 was 12 weeks after W_1 and W_3 was 16 weeks after W_2. In establishing the causal relationships, three models were tested (M_1, M_2 and M_3) (Figures 8; 9 and 19). This chapter presented the detailed interpretation of the key findings of the structural model on individual use of the BI system and provided an answer for RQ2. Innovative use was defined to occur when users can use more advanced BI system features such as self-service tools, interactive visualization, predictive analytics, and drill down functionality to support their work and improve their individual performance (Li, Hsieh and Rai, 2013). This was tested using longitudinal data focusing on individual management accountants who have been using the BI system for two years or less. The W_1 has 94 responses, which then dropped to 66 on W_2 and finally W_3 had 59 responses. The decrease was caused by attrition which is a common phenomenon of the longitudinal study. The chapter has found, through analysis of responses from 59 management accountants in South Africa, that innovative use of BI system improves individual level of performance over time. Results show that innovative use and user satisfaction are significant over time for individual performance, such as improving productivity and decision-making effectiveness, while those who uses routine features may not improve productivity and decision-making effectiveness over time. This justifies the differentiation between various types of use.

The study presented in this chapter has made an important contribution by differentiating the type of use over time. Innovative use is the critical element of supporting the management accountants in their job performance and quality of decision making, while routine use may not support job performance and quality of decision making over time. Management accountants should be encouraged to move from routine use to innovative if they want to continue improving their performance.

Further, the chapter has made a significant methodological contribution by assessing innovative use of BI systems using a longitudinal approach. Causality is a critical topic within the IS academic researchers. However, the D&M IS success model has previously been researched using cross-sectional data. The current study has adopted the cross-lagged longitudinal approach to measure the impact of causal relationship of innovative use of BI systems on individual level performance of management accountants.

This chapter focused on the cross-lagged effects of BI system use, user satisfaction and individual performance of management accountants. The next chapter turns to the organisational level of focus and presents the results of the impacts of the adoption of BI systems on a balanced set of firm performance measures.

CHAPTER 8: THE ORGANISATIONAL USE AND IMPACT OF BUSINESS INTELLIGENCE SYSTEM

8.1 Empirical Results

In Chapter 6 and 7, the cross-sectional and longitudinal individual usage models were empirically tested. This Chapter analyses data collected from the empirical study of organisational usage and impacts. The RQ3 and RO3 *"To examine the extent to which organisational adoption of BI systems impacts on a balanced set of organisational performance measures both directly and indirectly through impacts on the sophistication of management control systems"* is investigated and empirically tested. A survey was conducted by means of distributing questionnaires to obtain opinions from executives who represent South African organisations. The data collected from various executives was used to test the hypothesised model of the organisational BI system success. The initial sections discussed the sample size, demographics, data screening and sample outliers of the respondents. In addition, the next sections present descriptive statistics, assessment of normality and sample adequacy of the empirical data analysed. Furthermore, the principal component analysis, reliability and validity, correlation matrix are performed before confirmatory factor analysis of the measurement model is analysed. Finally, the results of the structural model are discussed, and the conclusion presented.

8.1.1 Sample Size

An invitation was sent to 396 organisations to participate in the survey of the study (refer section 5.5.2). A total of 199 (a response rate =50.23%) organisations participated in the study. The relatively high response rate for the study reduces the threat of non-response bias[18]. Moreover, early (within first 5 days) and late respondents (in the last 5 days) were compared using t-tests and no differences in responses were observed, thus also suggesting non-response bias is of limited concern (Annexure G). However, four responses were eliminated due to a large number of data missing in the questionnaire. The final useable sample consisted of 195 observations with sufficient data for meaningful statistical analysis, resulting in a response rate of 49.24%.

[18] For purposes of testing non-response bias, the strategy of comparing early and late respondents (as proxies for non-respondents) was employed (Annexure G).

8.1.2 Demographics

Descriptive statistics are presented to provide an overview of the sample before testing the SEM model. "The demographic profile of the respondents is presented below in Table 62". All 195 useable respondents provided their demographic information.

The results in Table 62 display that 36.9% of the responding executives are Finance Directors of the companies, and 34.4% with 11-15 years of experience within their organisation. Across all companies, the respondents were considered sufficiently senior and as having relevant experience to respond meaningfully about their organisations. The responding organisations were relatively large with 38.5% having between 1000 and 4999 employees and more than half having over 5000 employees. The overwhelming majority, 93.8%, of organisations earn revenue in excess of R500 million, and 55.4% of organisations have been operational for more than 36 years. The results also indicate 19.5% are organisations in the service sector. So, the sample is reflective of large organisations operating in South Africa with a good representation of companies across all the industry sectors. Just over one quarter of the responding organisations were using SAP business objects as their BI system (26.7%), and over 60% of responding organisations report that BI has been in use for more than six years within the organisations. Results further indicate that most of the organisations report that they (81.5%) have been utilising BI systems to support almost all their business processes and functions, suggesting a fairly wide diffusion of BI.

Table 62 Demographics Information

Demographics	Category	Frequency	Percentage
Number of employees	101-499	2	1.0
	500-999	10	5.1
	1000-4999	75	38.5
	5000-9999	66	33.8
	>10000	42	21.5
Annual revenue earned by organisation	R51-R100 million	0	0
	R101-R150 million	1	0.5
	R151-R200 million	3	1.5
	R201-R499 million	8	4.1
	>R500 million	183	93.8
	Manufacturing	36	18.5
	Utilities and energy	12	6.2
	Logistics	17	8.7
	Retail	15	7.7
	Telecommunications	6	3.1

Demographics	Category	Frequency	Percentage
Sector in which your organisation operates.	Pharmaceutical	12	6.2
	Public sector	6	3.1
	Service	38	19.5
	Finance	34	17.4
	Mining	19	9.7
Job title	Chief Financial Officer	42	21.5
	Management Accountant	23	11.8
	Finance Director	72	36.9
	Managing Director	20	10.3
	Executive Director	38	19.5
Years of experience in the organisation	<5 years	19	9.7
	6-10 years	46	23.6
	11-15 years	67	34.4
	> 16 years	63	32.3
Number of years company has been operational	<5 years	2	1.0
	6-10 years	24	12.3
	11-15 years	20	10.3
	16-20 years	4	2.1
	21-25 years	5	2.6
	26-30 years	10	5.1
	31-35 years	22	11.3
	> 36 years	108	55.4
Number of years company has been using BI system	<1 year	14	7.2
	1-2 years	16	8.2
	3-5 years	45	23.1
	6-9 years	67	34.4
	>10 years	53	27.2
BI system currently being used by the organisation	SAP business object	52	26.7
	SAS	13	6.7
	Oracle	16	8.2
	Microsoft	25	12.8
	MicroStrategy	12	6.2
	IBM Cognos	6	3.1
	Qlikeview	15	7.7
	SAGE	23	11.8
	Sisense	8	4.1
	Synergy	1	0.5
	Clear Analytics (Excel based)	19	9.7
	Other	5	2.6
Percentage of work done through the BI system	26-50% (some)	0	0
	51-75% (most)	36	18.5
	76-100% (almost all)	159	81.5

Overall, the demographic data suggests that respondents cover a large number of organisations operating in South Africa with a good representation of companies across all the industry sectors. These indicate that BI systems executives are familiar with the implementation. Most of the organisations have been using BI systems for more than five years, which provides a fair representation of the time over which BI systems have been diffusing across the organisations. Furthermore, most of the management functions are being supported by the BI system implemented. This is an indication on how BI systems are widely diffused within the organisations. Therefore, data analysis could proceed to the next step.

8.1.3 Data Screening

Data collected were analysed using the "Statistical Package for the Social Sciences (SPSS) Version 25", screened for missing data. There were two responses with few data missing, the items affected were system quality, service quality and routine use (Table 63). The missing data were handled using the median of nearby points method. The median of the nearby points method is calculated using the average of the nearby surrounding values (Byrne, 2013). "These numbers are calculated using a span of nearby points option in the SPSS program". The median is computed considering all values of the items construct data from the upper and lower, the calculated value is used to replace the missing value (Hair et al., 2010).

Table 63 Responses with missing data

Item	Number of missing responses
Strategy (ST) Item 4	1
Business process (NBP) item 5	1

8.1.4 Sample Outliers

"Outliers are defined as data points that differ significantly from other observations" (Hair et al., 2010). To identify potential outliers, any responses that are unusually high or unusually low values were screened (Tarka, 2018). Extreme responses might suggest that the respondents are not from the same population. The extreme values are typically a response more than three standard deviations above or below the sample mean (Hair et al., 2010). Standardised scores on an item reflect the "number of standard deviations from the mean". The standardised scores of each respondent were examined on each questionnaire item and none were identified as outliers. This is not surprising, given that the questionnaire items were all answered on a given scale.

8.1.5 Descriptive Statistics of Construct Items

The constructs investigated in this study were measured using two different scales. Firstly, the constructs, such as adoption of BI system, sophistication of informal control, quality of the board, strategy, organisational structure, and organisational environment were measured on seven-point Likert scales where the value of 1 corresponds to "Strongly disagree" and the value of 7 corresponds to "Strongly Agree". Secondly, the remaining constructs, such as "sophistication of formal control", "customer performance", "business process", "learning and development" and "financial performance" were measured using seven-point Likert scales where the value of 1 corresponds to "Much worse than expected" and the value of 7 corresponds to "Much better than expected". The mid-point of the seven-point Likert scale is therefore "4". Thus, values below 4 suggest most respondents perceived outcomes as worse than expected. Values between 4 and 4.5 indicate a more neutral response where outcomes were neither worse nor better than expected, while means above 4.5 reflect most holding the view that outcomes were better than expected. The summary of descriptive statistics per construct are presented in Table 64.

Table 64 Summary of Descriptive Statistics per Construct

Variables	Minimum	Maximum	Mean	Std. deviation	Skewness	Kurtosis
Adoption of BI system (AD)	1.9	6.9	5.8250	1.23759	-1.74561	2.17566
Quality of the board (QB)	2.0	6.7	4.7094	1.64484	-0.33204	-1.53097
Organisational environment (OE)	2.2	6.8	5.3282	1.45994	-1.23973	0.00911
Strategy (ST)	1.2	6.7	4.5872	1.85587	-0.28369	-1.70654
Organisational structure (OS)	1.5	6.8	4.9641	1.43052	-1.04118	-0.39161
Business process (NBP)	1.4	6.8	4.2072	1.87522	-0.02415	-1.69757
Customer (NCR)	1.8	6.5	4.5321	1.51324	-0.44407	-1.51295
Organisational learning (NOL)	1.3	6.7	4.5573	1.74145	-0.42439	-1.49544
Financial performance (FP)	1.4	6.6	4.4369	1.78304	-0.09933	-1.60455
Management Reporting (MR)	1.4	4.3	3.2703	0.66808	-1.04881	-0.08059

Variables	Minimum	Maximum	Mean	Std. deviation	Skewness	Kurtosis
Sophistication of formal control (SFC)	1.2	6.6	4.6554	1.56212	-0.74417	-0.83051
Sophistication of in-formal control (SIC)	1.8	6.8	5.0085	1.27489	-0.88612	-0.23648

8.1.5.1 Adoption of BI system (AD)

The adoption of BI system scale was constructed to extract information on organisational beliefs that the BI system supports various management functions (i.e. financial management, sales, marketing, customer relations, human resources, supply chains management, project management and production management). The overall mean is 5.8 and standard deviation is 1.24 as presented in Table 64. Eight items were adapted from prior work related to diffusion of IS systems more generally (Liang et al., 2007; Cooper and Zmud, 1990), and were "measured using a 7-point Likert scale". As illustrated in Table 65, the mean of items ranges from 5.74 (1.18) to 5.92 (1.67). This suggests that most "respondents tend to mostly agree that the BI system" is supporting various management functions within the organisations.

Table 65 Statistical Results of AD Items

Variable	Obs	Mean	Std. Dev.	Min	Max
AD1	195	**5.79**	1.49	1	7
AD2	195	**5.87**	1.28	1	7
AD3	195	**5.89**	1.32	1	7
AD4	195	**5.92**	1.18	1	7
AD5	195	**5.74**	1.52	1	7
AD6	195	**5.77**	1.67	1	7
AD7	195	**5.81**	1.37	1	7
AD8	195	**5.81**	1.20	1	7

8.1.5.2 Quality of the board (QB)

Quality of the board construct was conceptualised to obtain information on organisational beliefs on the board's role in monitoring performance and holding executives accountable. The overall mean is 4.7 and standard deviation is 1.65 as presented in Table 64 above. Three items were adopted for this quality of board measure from past work (Chenhall, 2003;2006), and "measured using a 7-point Likert scale". As illustrated in Table 66, the mean of items ranges from 4.66 (1.71) to 4.74 (1.84). This suggests that “most respondents tend to agree” with the items measuring the quality of the board.

Table 66 Statistical Results of QB Items

Variable	Obs	Mean	Std. Dev.	Min	Max
QB1	195	**4.40**	1.84	1	7
QB2	195	**4.73**	1.72	1	7
QB3	195	**4.66**	1.71	1	7

8.1.5.3 Organisational environment (OE)

The organisational environment construct was conceptualised to obtain information on how dynamic, turbulent, and competitive an organisation perceives the environment in which it operates. The overall mean is 5.3 and standard deviation is 1.46 as presented in Table 64. Six items were adapted from prior work related to control variables (Chenhall, 2003;2006) and “measured using a 7-point Likert scale”. As illustrated in Table 67, the mean of items ranges from 4.96 (1.53) to 5.60 (1.72). This suggest that most respondents tend to agree that they operate in dynamic and competitive environments.

Table 67 Statistical Results of OE Items

Variable	Obs	Mean	Std. Dev.	Min	Max
OE1	195	**5.60**	1.71	1	7
OE2	195	**5.39**	1.56	2	7
OE3	195	**5.39**	1.53	2	7
OE4	195	**5.26**	1.53	2	7
OE5	195	**5.35**	1.61	1	7
OE6	195	**4.96**	1.72	1	7

8.1.5.4 Strategy (ST)

The strategy construct is conceptualised to obtain information on the strategic orientation of the organisation with regards to innovation, product or service differentiation and cost control. The overall mean is 4.59 and standard deviation is 1.86 as presented in Table 64 above. Six items for strategy were adopted from prior work related to control variables (Chenhall, 2003;2006) and were “measured using a 7-point Likert scale”. As illustrated in Table 68, the mean of items ranges from 4.34 (1.77) to 4.80 (2.16). This suggests that most respondents tend to agree that they emphasise both product/service differentiation and cost control.

Table 68 Statistical Results of ST Items

Variable	Obs	Mean	Std. Dev.	Min	Max
ST1	195	**4.64**	2.16	1	7
ST2	195	**4.47**	1.77	1	7
ST3	195	**4.78**	2.11	1	7
ST4	195	**4.80**	1.97	1	7
ST5	195	**4.49**	2.07	1	7
ST6	195	**4.34**	1.87	1	7

8.1.5.5 Organisational structure (OS)

The organisational structure construct was conceptualised to obtain information on whether organisations had a flexible structure emphasising employee independence over their work. The overall mean is 4.96 and standard deviation is 1.43 as presented in Table 64. above. Four items were adopted from prior work related to control variables (Chenhall, 2003;2006) and "measured using a 7-point Likert scale". As illustrated in Table 69, the mean of items ranges from 4.72 (1.47) to 5.20 (1.65). This suggests that most respondents tend to agree they have a flexible organisational structure.

Table 69 Statistical Results of OS Items

Variable	Obs	Mean	Std. Dev.	Min	Max
OS1	195	**5.20**	1.65	1	7
OS2	195	**5.12**	1.51	1	7
OS3	195	**4.72**	1.47	1	7
OS4	195	**4.82**	1.65	1	7

8.1.5.6 Business process performance (NBP)

The business process performance measure was constructed in this thesis to extract information on organisational beliefs in the improvement of business process performance. The overall mean is 4.2 and standard deviation is 1.88 as presented in Table 64. above. Six items for business process performance were adopted from prior work related to organisational performance (Kaplan and Norton, 1992, 2001;2006) and "measured using a 7-point Likert scale". As illustrated in Table 70, the mean of items ranges from 4.10 (1.52) to 4.49 (2.12). This suggests that respondents' perceptions on the outcome of business process performance has, on average, been somewhat neutral.

Table 70 Statistical Results of NBP Items

Variable	Obs	Mean	Std. Dev.	Min	Max
NBP1	195	**4.10**	2.02	1	7
NBP2	195	**4.18**	1.91	1	7
NBP3	195	**4.21**	2.05	1	7
NBP4	195	**4.17**	2.12	1	7
NBP5	195	**4.38**	1.96	1	7
NBP6	195	**4.49**	1.52	1	7

8.1.5.7 Customer performance (NCR)

The customer performance measure was constructed in this thesis to extract information on organisational beliefs in the improvement of customer performance. The overall mean is 4.53 and standard deviation is 1.51 as presented in Table 64, above. Four items were adopted from prior work on performance (Kaplan and Norton, 1992, 2001;2006) and "measured using a 7-point Likert scale". As illustrated in Table 71, the mean of items ranges from 4.42 (1.54) to 4.66 (1.82). This suggests that respondents' perceptions on the outcome of customer performance has, on average, been somewhat better than expected.

Table 71 Statistical Results of NCR Items

Variable	Obs	Mean	Std. Dev.	Min	Max
NCR1	195	**4.42**	1.60	1	7
NCR2	195	**4.61**	1.54	1	7
NCR3	195	**4.44**	1.82	1	7
NCR4	195	**4.66**	1.65	1	7

8.1.5.8 Organisational feedback and learning (NOL)

The organisational feedback and learning performance measure was constructed in this thesis to extract information on organisational beliefs into the improvement of feedback and learning. The overall mean is 4.56 and standard deviation is 1.74 as presented in Table 64, above. Four items were adopted from prior work related to organisational performance (Kaplan and Norton, 1992, 2001;2006) and "measured using a 7-point Likert scale". As illustrated in Table 72, the mean of items ranges from 4.53 (1.54) to 5.16 (1.96). This suggests that respondents' perceptions on the outcome of feedback and learning performance has, on average, been somewhat better than expected.

Table 72 Statistical Results of NOL Items

Variable	Obs	Mean	Std. Dev.	Min	Max
NOL1	195	**4.53**	1.95	1	7
NOL2	195	**5.16**	1.54	1	7
NOL3	195	**4.61**	1.72	1	7
NOL4	195	**4.53**	1.96	1	7

8.1.5.9 Financial performance (FP)

The financial performance scale was constructed in this thesis to extract information on organisational beliefs in the improvement of financial performance. The overall mean is 4.44 and standard deviation is 1.78 as presented in Table 64 above. Six items were adopted from prior work related to organisational performance (Kaplan and Norton, 1992; Elbashir et al., 2008; Kallunki et al., 2011) and "measured using a 7-point Likert scale". As illustrated in Table 73, the mean of items ranges from 4.33 (1.55) to 5.27 (2.19). This suggests that respondents' perceptions on the outcome of financial performance has, on average, been better than expected.

Table 73 Statistical Results of FP Items

Variable	Obs	Mean	Std. Dev.	Min	Max
FP1	195	**4.33**	2.11	1	7
FP2	195	**4.42**	1.55	1	7
FP3	195	**4.36**	1.94	1	7
FP4	195	**4.58**	1.88	1	7
FP5	195	**4.50**	2.19	1	7
FP6	195	**5.27**	1.52	1	7

8.1.5.10 Sophistication of formal control (SFC)

The sophistication of formal control scale was constructed in this thesis to extract information on organisational beliefs in the improvement of sophistication of formal control within the organisation. The overall mean is 4.66 and standard deviation is 1.56 as presented in Table 64 above. Ten items for sophistication of formal control were adopted from prior work related to organisational performance (Elbashir et al., 2008; Kallunki et al., 2011; Granlund, 2011) and "measured using a 7-point Likert scale". As illustrated in Table 74, the mean of items ranges from 4.48 (1.39) to 4.77 (1.81). This suggests that respondents' perceptions on the outcome of improvement of sophistication of formal control has, on average, been somewhat better than expected.

Table 74 Statistical Results of SFC Items

Variable	Obs	Mean	Std. Dev.	Min	Max
SFC1	195	**4.66**	1.58	1	7
SFC2	195	**4.66**	1.81	1	7
SFC3	195	**4.70**	1.64	1	7
SFC4	195	**4.69**	1.69	1	7
SFC5	195	**4.56**	1.43	1	7
SFC6	195	**4.56**	1.73	1	7
SFC7	195	**4.37**	1.55	1	7
SFC8	195	**4.48**	1.41	1	7
SFC9	195	**4.77**	1.47	1	7
SFC10	195	**4.65**	1.39	1	7

8.1.5.11 Sophistication of informal control (SIC)

The sophistication of informal control scale was constructed in this thesis to extract information on organisational beliefs on improvements experienced in the sophistication of their informal controls. The overall mean is 5.01 and standard deviation is 1.28 as presented in Table 64 above. Nine items were adopted from prior work related to organisational performance (Elbashir et al., 2008; Kallunki et al., 2011; Granlund, 2011) and "measured using a 7-point Likert scale". As illustrated in Table 75, the mean of items ranges from 4.75 (1.39) to 5.51 (1.79). This suggests that respondent's perceptions on the outcome of sophistication of informal control has, on average, been somewhat better than expected.

Table 75 Statistical Results of SIC Items

Variable	Obs	Mean	Std. Dev.	Min	Max
SIC1	195	**4.96**	1.40	1	7
SIC2	195	**5.21**	1.39	1	7
SIC3	195	**5.04**	1.45	1	7
SIC4	195	**5.15**	1.52	1	7
SIC5	195	**5.51**	1.79	1	7
SIC6	195	**5.10**	1.66	1	7
SIC7	195	**4.75**	1.64	1	7
SIC8	195	**5.05**	1.42	1	7
SIC9	195	**5.23**	1.48	1	7

8.1.6 Assessment of Normality

Table 64 above indicates "Skewness and Kurtosis coefficients" of all the constructs appearing in the model. The value for "skewness and kurtosis between -2 and +2 is considered an acceptable indication of normality" (George and Mallery, 2010). The results summarized in

Table 64 indicate an acceptable normality[19], given that the values of most “kurtosis and skewness are between -2 and +2”. However, the “central limit theorem stipulates that deviation from the normality has little effect on the data for large sample size” (Muzaffar, 2016). Since deviation from normality is not an issue, the analysis could confidently proceed with the use of principle component analysis to determine if the items are loading with the latent constructs.

8.1.7 Sample Adequacy

The adequacy of the sample was measured using “Kaiser-Meyer-Olkin (KMO)” test as developed by Kaiser and Rice (1974). According to Field (2009), KMO measures sampling characteristics of the “ratio of the squared correlation between variables to the squared partial correlation between variables”. The patterns of correlations vary between 0 to 1, and if the value of the KMO measure is close to 1, the correlations should produce reliable factors (Field, 2009). Values that are between 0.5 and 0.7 are poor, between 0.7 and 0.8 are good, valued between 0.8 and 0.9 are great, and above 0.9 are excellent (Abdi, 2010). The results of this study are illustrated below in Table 76, which indicates the KMO result as 0.90. The results of KMO indicates that the sampling adequacy falls withing the great range. This indicate that the sampling “size is adequate to yield reliable factors”.

Table 76 KMO and Bartlett’s Test

“Kaiser-Meyer-Olkin Measure of Sampling Adequacy”.	0.897
“Approx”. “Chi-Square”	13512.69
df	1770
Sig.	0.000

Bartlett (1954) developed a test that “analysed whether the correlations between survey items is large enough for appropriate factor analysis”. This test indicates the strength of the relationship within variables. The results of the research indicate that the Chi-square is 13512.69 and its significance is less than 0.001. This indicates that the sample size of the research is sufficient to proceed with the “principal component analysis (PCA)”.

[19] Although survey data may sometimes be subject to polarised views, bimodal distributions, J curves and other anomalies, the data distributions were found acceptable.

8.1.8 Principal Components Analysis (PCA)

Factor analysis (principal component) was conducted using the orthogonal rotation (Varimax) method. “This method was selected because it essentially captures the components with high eigenvalues and organises by order of importance (Hair et al., 2011)”. Factor analyses function on the assumption that measurable and observable variance can be reduced to a few latent variables that share common variance (Vonglao, 2017). This is known as the reduction of dimensionality. The unobserved factors are not measured directly but they are critical in an hypothetical model. The use of Exploratory Factor Analysis (EFA) using a technique such as PCA is the first step in constructing scales (Hair et al., 2011). EFA is considered a useful first step prior to any Confirmatory Factor Analysis (CFA) and important to carry out at the early-stages of developing scales. EFA offers an opportunity to a researcher to explore the main dimension to produce a theory or model from latent constructs represented by set of items (Sangthong, 2020). In this study, an exploratory analysis was chosen as there is not enough research evidence of the use and impacts of BI system on individual management accountants from the South African context to move directly to confirmatory testing, and therefore an initial exploratory approach was warranted.

Hair et al. (2010) stated that for a construct to be labelled a factor, it should have at least three variables (i.e., scale items), but this can also depend on how the study has been designed. A variable should reflect only one construct and therefore should not have a high relationship with more than one factor (i.e., cross-loading of an item onto multiple factors is problematic) (Murray, 2013). The use of a rotation matrix maximises high item loadings, while minimising low item cross-loadings, which produces a more interpretable and simplified solution. The rotation on SPSS can be carried out using five methods such as varimax, quartimax, equamax, direct oblimin and promax (Sangthong, 2020). This study chose to use varimax rotation in order to maximise high item loadings. To make the output easier to read, loadings of less than 0.40 were suppressed from the output. This study has 195 responses, and the factor loading was considered to be small at 0.50 or less, with higher loadings considered significant at the $p < 0.05$ level (Henseler, Ringle and Sinkovics, 2015). A loading represents the relationship between the item (variable) and the factor. If less than 50% of an item’s variance is shared with a factor (i.e., the loading is less than 0.5), then the item is not considered a reliable measure of the underlying factor (construct). Therefore, items/variables with primary factor loadings of less than 0.50 were thus eliminated from the study (Mohamad et al., 2014). Table 77 presents the results of factor analysis of the measurement items for the study of adoption of BI systems on performance outcomes within organisations. The table indicates the final stable PCA solution after a few iterations in which some items were dropped based on low primary loadings (i.e., less than 0.50) or high cross-loadings (i.e., greater than 0.40). The items that were dropped are explained below. The principal component analysis indicate that 11 factors were extracted on 45 items. The total variance explained is 83%. The lowest item loading was 0.690.

Table 77 Principal Component Analysis

"Rotated Component Matrix"											
"Component"											
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
AD1	.824										
AD2	.851										
AD3	.826										
AD4	.825										
AD5	.770										
AD6	.825										
AD7	.786										
QB1										.859	
QB2										.854	
QB3										.870	
OE1								.706			
OE2								.716			
OE3								.762			
OE4								.690			
OE5								.704			
ST1		.904									
ST2		.862									
ST3		.901									
ST4		.882									
ST5		.893									
ST6		.835									
OS1									.768		
OS2									.745		
OS3									.770		
OS4									.734		
NBP1				.920							
NBP2				.885							
NBP3				.889							
NBP4				.820							
NBP5				.883							
NCR1							.874				
NCR2							.900				
NCR3							.839				
NCR4							.905				
NOL1											.818
NOL3											.878
NOL4											.839
FP1						.888					
FP2						.922					
FP3						.839					

“Rotated Component Matrix”											
“Component”											
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
FP4						.899					
FP5						.860					
SFC1			.823								
SFC2			.877								
SFC3			.840								
SFC4			.883								
SFC6			.844								
SIC1					.761						
SIC3					.773						
SIC4					.831						
SIC6					.849						
SIC7					.818						
SIC8					.845						
Rotation Method: Varimax with Kaiser Normalization.											
Rotation converged.											
Total Variance Explained 83%											

Adoption of the BI system (AD) was measured through eight items. As per Table 77, seven items loaded highly onto the same factor with cross-loading below 0.40 on other factors. However, one item for adoption of BI system was dropped (AD8) due to the item loading below 0.50.

Quality of the board (QB) was measured using three items. As per Table 77, three items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. No items for quality of the board needed to be dropped.

Organisational environment (OE) was measured through six items. As per Table 77, five items loaded highly onto the same factor and did not cross-load above 0.40 onto other factors. One item for Organisational environment (OE6) was however dropped because the item loading was less than 0.50. This is perhaps not surprising as this item captured the actions of competitors which may not have been relevant for all organisations in the sample.

Strategy (ST) was measured using six items. As per Table 77, six items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. No items for strategy needed to be dropped.

Organisational structure (OS) was measured through six items. As per Table 77, four of the six items loaded highly onto the same factor and did not cross-load above 0.40 onto other factors.

Two items for Organisational structure were however dropped, OS5 and OS6, because their loadings were below 0.50.

Business process performance (NBP) was measured through six items. As per Table 77, five items loaded highly onto the same factor and did not cross-load above 0.40 onto other factors. However, one item for business process performance (NBP6) was dropped because the item loading was less than 0.50.

Customer performance (NCR) was measured using four items. As per Table 77, four items loaded highly onto the same factor and none cross-loaded above 0.40 onto other factors. No items for customer performance needed to be dropped.

Organisational feedback and learning performance (NOL) was measured through four items. As per Table 77, three items loaded highly onto the same factor and did not cross-load above 0.40 onto other factors. One item for organisational feedback and learning performance was however dropped, which was NOL2. This item was dropped because the item loading was less than 0.50.

Sophistication of formal control (SFC) was measured through ten items. As per Table 77, five items loaded highly onto the same factor and did not cross-load above 0.40 onto other factors. However. five items for sophistication of formal control were dropped, namely, SFC5, SFC7, SFC8, SFC9 and SFC10 because their item loadings were less than 0.50.

Sophistication of informal control (SIC) was measured through nine items. As per Table 77, six items loaded highly onto the same factor and did not cross-load above 0.40 onto other factors. However, three items for sophistication of informal control were dropped, namely, SIC2, SIC5 and SIC9 because their item loadings were less than 0.50.

Altogether, the underlying factor structure extracted by the PCA provided preliminary confirmation of the hypothesised measurement model which consisted of 11 multi-item constructs. The analysis could then proceed to examine the reliability of the scales, based on their remaining measurement items.

8.1.9 Scale Reliability and Validity

It is evident that for the scale to be valid and have practical usefulness, it must be reliable (Byrne, 2013). The reliability is the ability of the scale to produce the same results if it is used in the same conditions with the same objectives (Hair et al., 2010). In this study, “the scale used 11 factors to measure the proposed research conceptual framework", namely adoption of BI system, quality of board, organisational environment, strategy, organisational structure, "business process performance", "customer performance", organisational feedback and learning performance, "financial performance", sophistication of formal control and sophistication of informal control. The quality of board, organisational environment, strategy, and organisational structure were used as the control variables in the model. Table 78 presents the results of "Cronbach's alpha", "Average Variance Extracted (AVE) and Composite Reliability (CR)". In measuring the reliability, the "Cronbach's alpha was used". The scale is regarded as reliable if the "Cronbach's alpha is 0.70 and above" (Hair et al., 2010). Table 78 indicates that the "Cronbach's alpha" ranges from 0.776 to 0.969, this is "above the recommended value of 0.70". The CR ranges from 0.84 to 0.97, which is above the threshold of 0.70. In addition, the AVE for each construct was calculated. The AVE has a minimum value of 0.51 which is more than the recommended 0.50 threshold.

Table 78 Results of Reliability and Validity

						Composite scores	
Variables	**Number of initial items**	**Number of surviving items**	**Cronbach's alpha**	**Average variance explained (AVE)**	**Composite reliability (CR)**	**Mean**	**Standard deviation**
Adoption (AD)	8	7	0.968	0.80	0.97	5.8250	1.23759
Quality of the board (QB)	3	3	0.929	0.74	0.90	4.7094	1.64484
Organisational environment (OE)	6	5	0.961	0.51	0.84	5.3282	1.45994
Strategy (ST)	6	6	0.969	0.77	0.95	4.5872	1.85587
Organisational structure (OS)	6	4	0.926	0.57	0.84	4.9641	1.43052
Business process (NBP)	6	5	0.939	0.84	0.96	4.2072	1.87522
Customer (NCR)	4	4	0.776	0.78	0.94	4.5321	1.51324
Organisational learning (NOL)	4	3	0.849	0.80	0.92	4.5573	1.74145
Financial performance (FP)	6	5	0.939	0.82	0.96	4.4369	1.78304
Sophistication of formal control (SFC)	10	5	0.902	0.82	0.96	3.2703	0.66808
Sophistication of in-formal control (SIC)	9	6	0.912	0.65	0.92	4.6554	1.56212

8.1.10 Correlation Matrix of Composite Scores

Following the above tests which provide evidence of scale reliability and convergent validity (through examination of loadings and AVE values), tests of construct validity also require an additional test for discriminant validity (Sangthong, 2020). The inter-correlation has been calculated and presented in Table 79. The principle of "discriminant validity" requires that the measures of a construct should correlate more highly with each other and not correlate as highly with measures of other constructs (Hair et al., 2010). This principle can be tested by comparing "inter-construct correlations" with the AVE or "square root of AVE of each construct". The "square roots of AVE" are data presented along the diagonal position for each variable construct. The "square root of AVE" of each variable construct is greater than the correlation coefficient between variables (Sangthong, 2020). The "discriminant validity" is thus confirmed i.e., constructs share more variance with their own items than with other constructs in the model. All the results confirm the "reliabilities", "convergent" and "discriminant validities" of the constructs. The model is further tested in the next section.

Table 79 Results of Matrix of Composite Scores

	Mean (S.D.)	AD	QB	OE	ST	OS	NBP	NCR	NOL	FP	SFC	SIC
AD	5.8 (1.2)	**0.892**										
QB	4.7 (1.7)	0.404**	**0.861**									
OE	5.3 (1.5)	0.664**	0.403**	**0.716**								
ST	4.6 (1.9)	0.423**	0.382**	0.480**	**0.880**							
OS	5.0 (1.4)	0.614**	0.295**	0.600**	0.381**	**0.754**						
NBP	4.2 (1.9)	0.358**	0.296**	0.454**	0.309**	0.406**	**0.915**					
NCR	4.5 (1.5)	0.332**	0.070	0.292**	0.146*	0.140	0.064	**0.885**				
NOL	4.6 (1.7)	0.376**	0.365**	0.386**	0.268**	0.429**	0.382**	0.114	**0.891**			

	Mean (S.D.)	AD	QB	OE	ST	OS	NBP	NCR	NOL	FP	SFC	SIC
FP	4.4 (1.9)	0.322**	0.221**	0.435**	0.314**	0.220**	0.218**	0.380**	0.136	**0.904**		
SFC	4.7 (1.6)	0.488**	0.281**	0.510**	0.114	0.512**	0.315**	0.034	0.390**	0.136	**0.905**	
SIC	5.0 (1.3)	0.299**	0.241**	0.354**	0.109	0.337**	0.268**	0.095	0.302**	0.069	0.302**	**0.804**

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

*. "Correlation is significant at the 0.05 level (2-tailed)".

8.2 Results of Model Testing

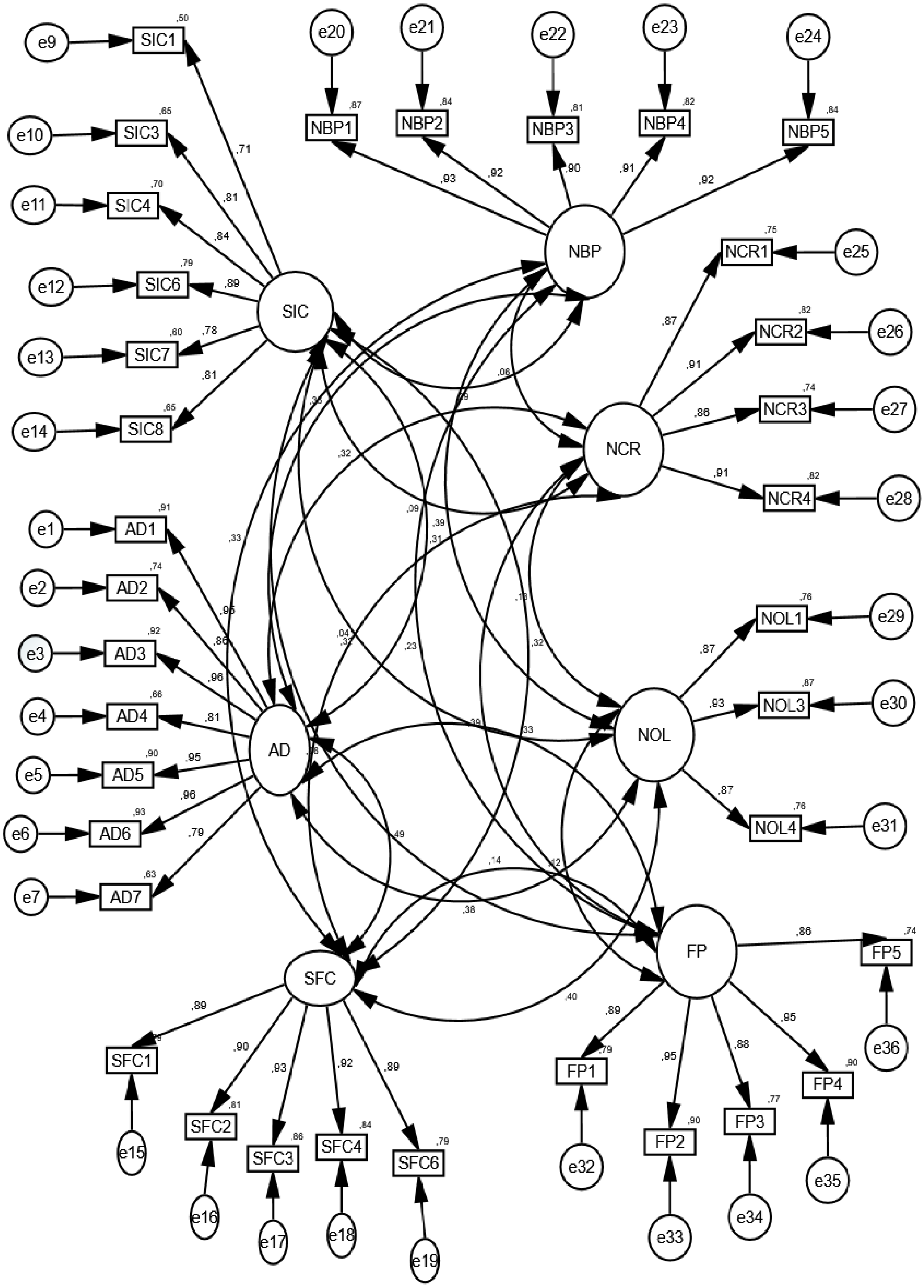
This section proceeds to formally test the study's measurement and "structural model". Before the hypothesised "structural model can be tested", it is advisable to perform a CFA as a final test of the "measurement model" in order to identify if all the items are loading properly on the hypothesised constructs in the model. The CFA was used to test the hypothesis "with respect to sources of variability responsible for the commonality among a set of scores". The CFA analysis excluded the control variables and used only the 35 items measuring the main variables that had survived from the "exploratory factor analysis (PCA) stage". The CFA was used to confirm that the proposed factor structure is a good fit to the data.

Following the CFA, the second step is to use "Structural Equation Modelling (SEM)" to test the hypotheses represented by relationship between "independent and dependent variables", i.e., the "structural model". The SEM model is conducted using AMOS version 25; AMOS is easier to use as the path diagrams are simplified compare to other software such as LISREL, STATA etc. (Sangthong, 2020). The CFA step proceeds next.

8.2.1 CFA Model Results

The CFA was used to assess the relationships between various constructs within the developed theoretical model. In assessing the model, it is important to assess the "measurement model fit" and measure the "validity of the model" being tested. In the process of "evaluating the measurement model in the CFA", there is no need to differentiate between exogenous and endogenous constructs. Differentiating between exogenous and endogenous constructs is only necessary during the structural model testing. Figure 34 indicates all variables being linked together and the measured variables (construct items) are shown in rectangular shapes. The covariance is illustrated in Figure 34 by two headed arrows, the causal relationship is indicated by one-headed arrows. The model illustrated in Figure 34 does not include the controls, i.e., quality of the board, organisational environment, strategy, and organisational structure. Therefore, the model in Figure 34 only focuses on the adoption of BI system, sophistication of formal control, sophistication of informal control, "non-financial performance (business process performance", "customer performance" and organisational feedback and learning) and financial performance. The 35 items that had survived from the exploratory factor analysis (PCA) stage reflected these variables.

Figure 34 CFA Measurement Model



8.2.2 Goodness of Fit Indices

The “maximum-likelihood method” was adopted to “estimate the model’s parameters” and all analysis was “conducted on covariance matrices”. There are model fit indices that need to be considered when analysing the model goodness-of-fit. The first step is to assess the Chi-square (χ^2) of the model being tested. The χ^2 was found to be high and the ratio of χ^2 / DF=15 is higher than the recommended 3. The examination of χ^2 for model fit may however lead one to reject the hypothesized model unnecessarily (Hair et al., 2010). “Even a small difference between the observed model and a good model fit might be found to be significant”. Table 80 indicates the CFA model fit indices as follows (GFI= 0.713; NFI=0.824; CFI=0.878; IFI=0.879; RMSEA=0.097; DF=539; TLI=0.865 and RFI=0.806). Although the CFA model test indicates that some “model fit indices” were not entirely satisfactory, the main objective of the CFA model was to check if all the items of the scale were loading on the hypothesized constructs and thereby to confirm construct validity and factor loadings (Serrano Archimi, Reynaud, Yasin and Bhatti, 2018). It was not meant to test the hypotheses among the constructs. The results indicate that all the items are loading appropriately and in line with theory. The factor loadings of this model range between 0.710 and 0.964, which is well above the prescribed threshold of 0.50. Therefore, no additional items need to be dropped. Moreover, taken together with the PCA and reliability tests, the measurement model was considered satisfactory. Therefore, analysis could proceed to test the structural model without further amending the measurement model.

Table 80 Results of Goodness of Fit Indices CFA and Structural Model

Fit Index	Recommended Value	CFA Results	Original Structural Model	Final Structural Model
Goodness-of-fit (GFI)	Less than 0.80 (No fit) Between [0.80-0.90] (acceptable) Above 0.90 (Perfect fit)	0.713	0.975	0.999
Normed fit index (NFI)	Less than .80 (poor) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.824	0.926	0.998
Comparative fit index (CFI)	Less than 0.90 (poor) Above 0.90 (good)	0.878	0.937	1
Incremental fit index (IFI)	Less than 0.90 (poor) Above 0.90 (good)	0.879	0.941	1
Root mean square error of	Less than 0.05 (good)	0.097	0.136	0.000

approximation (RMSEA)	Between [0.06-1] (acceptable) Above 1 (poor)			
Chi-square ($\chi2$ /DF)	Less than 3 (good) Between [3-5] (acceptable) Above 5 (poor)	15	4	2
Tucker-Lewis Index (TLI)	Less than 0.80 (poor) Between [0.80-0.90] (acceptable) Above 0.90 (good)	0.865	0.669	1
Relative Fit Index (RFI)	Less than 0.80 (poor) Between [.80-.90] (acceptable) Above .90 (good)	0.806	0.612	0.977

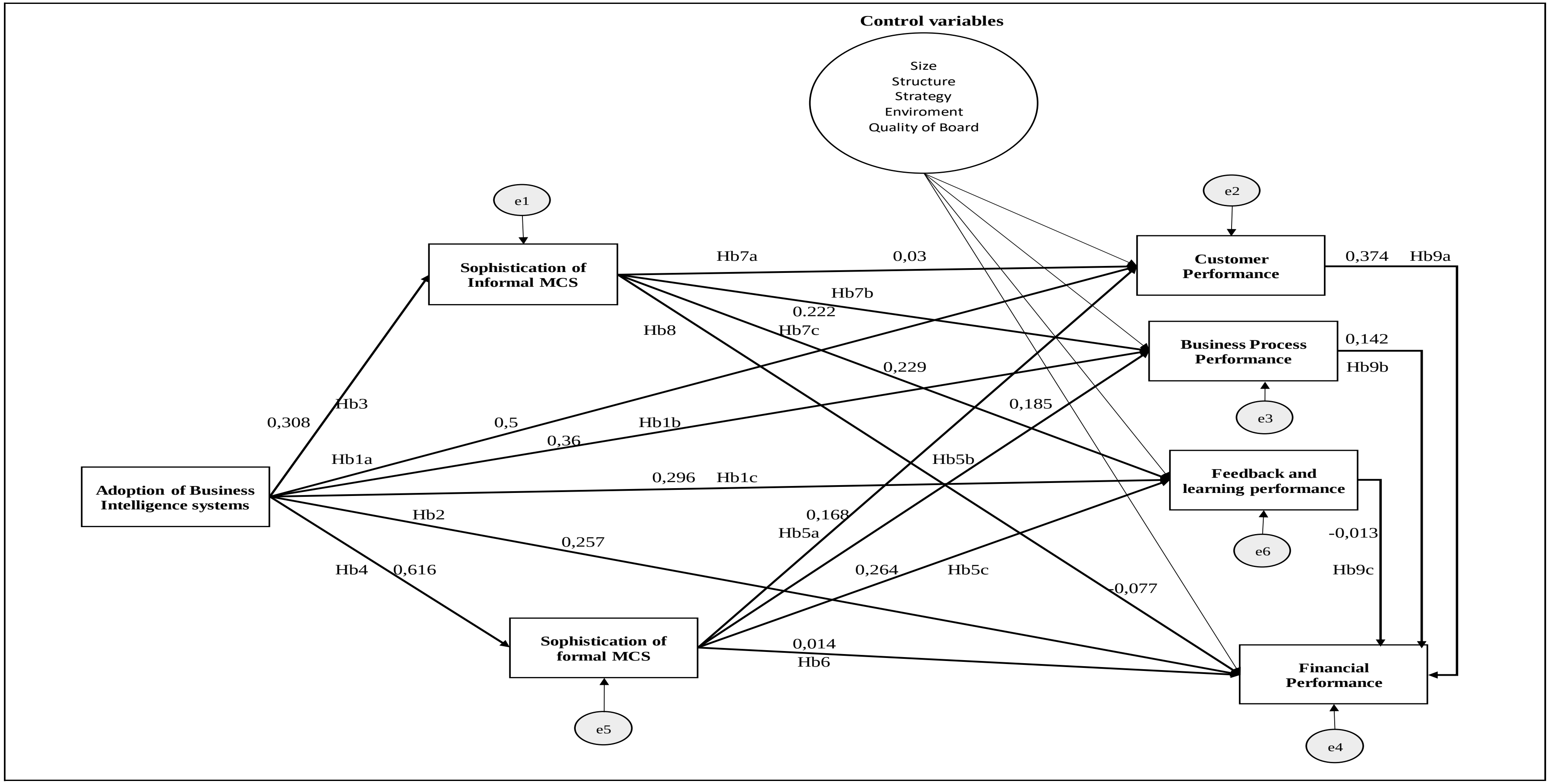
The next section tests the hypothesised model.

8.2.3 Original Structural Model Test

The next stage is to test the hypothesised "relationships between the exogenous and endogenous latent constructs" (refer Figure 13), which is done through the "test of the structural model". In this stage, "the relationships between independent and dependent variables" are specified. The "causal relationships between independent and dependent variable" are indicated through a one headed arrow. The covariance between independent variable is indicated by two headed arrows. In this study, only "free" pathways are modelled for hypothesised causal relationships between the variables that are being tested. The free pathways are left free to vary, there are no fixed pathways as dictated by previous studies (Serrano Archimi et al., 2018; Hair et al., 2010; Sangthong, 2020) in this model.

The test of the originally hypothesised model is illustrated in Figure 35. Results indicate that there could be improvements to model fit to test the causal relationships amongst variables. The original model indicates the $p<0.001$ which is significant, and the χ^2 / DF=4 which is "slightly higher than the recommended value of less than 3". The fit indices as illustrated in Table 80 are as follows: [GFI=0.975; NFI=0.926; CFI=0.937; IFI=0.941; RMSEA=0.136; TLI=0.669; RFI=0.612] indicating a less than ideal fit of the model, specifically for RMSEA, TLI and RFI. There is a need for the model improvement so that a better model fit can be achieved. In improving the model, some of the options available to the researcher are to consider whether any constructs or hypotheses may have to be dropped from the model that is being tested. Additional options include the drawing of error estimate co-variances to improve the model fit. The steps taken to improve model fit are described below.

Figure 35 Original Structural Model Test Results



8.2.3.1 Model improvement steps taken

In order to improve the model-fit, the following modifications were undertaken. These modifications were identified by examining the AMOS output.

The variances in the model were estimated, “there were no unmodelled variances that could be estimated in a revised model”. The variance “section contains no modification information”. There were, however, “possible regression weights and covariances that could be incorporated into a re-specified model that would result in minimal changes in the model fit chi-square test statistic”. The “modification index values were found in two pairs of residual covariances”. The covariance of e1 with e5 is expected to be 0.309 and e6 with e2 is expected to be 0.609. Awang, et al. (2015) stated that before allowing any pair of “error covariances to be estimated in a modified model”, “it is wise to reconsider the conceptual implications of model modification before you proceed further”.

In this case, the modification of covariance has a minor impact on the model, the chi-square fit moved from 4 to 2. Therefore, the covariances were drawn on two pair of modification indices as this would not change the meaning of the model.

In addition, quality of the Board, organisational environment, strategy and organisational structure are used as control variables on balanced set of organisational performance measures. However, it was decided in model revision to only include the control variables’ paths where a preliminary run found a significant effect and left out the paths where there was no relationship.

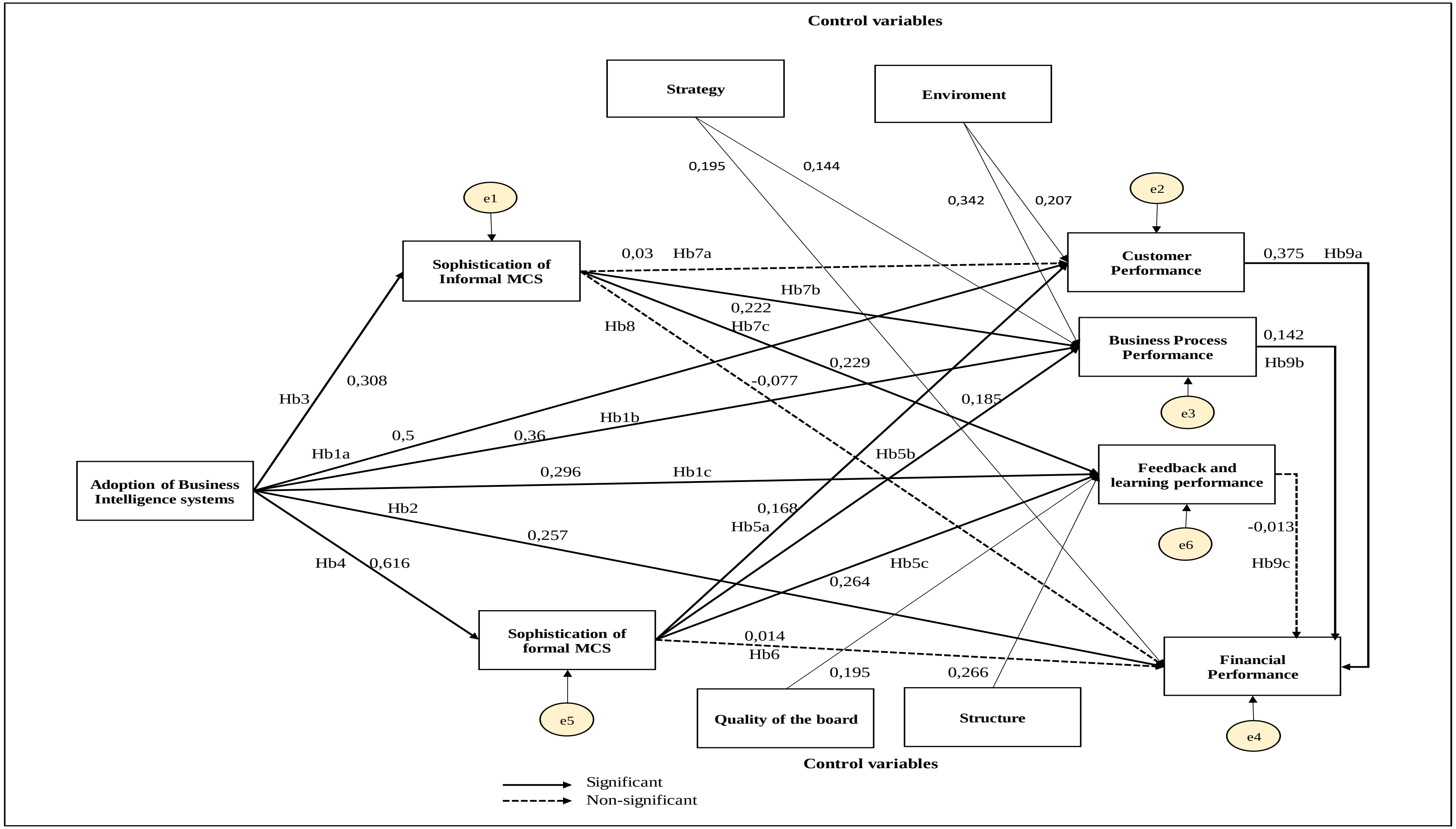
The results after this final improvement are presented as follow.

8.2.4 Final Model Testing

The results of final SEM AMOS model are presented in Figure 36.

The final model fit has p=0.762 which is not significant, compared to the default model, and the χ^2 / DF=2 is acceptable and is less than the recommended value of 3. Based on the second run of the model, the results of model fit have improved as presented in Table 80. The fit indices are as follows: [GFI=0.999; NFI=0.998; CFI=1; IFI=1; RMSEA=0.000; DF=2; TLI=1; RFI=0.977] indicating a good model fit in all the indices. The hypothesised relationships are presented in Figure 36.

Figure 36 Final Structural Model Test Results



The organisational model was developed to measure the extent to which organisational adoption of BI systems impacts a balanced set of organisational performance measures directly and indirectly through impacts on the sophistication of “management control systems”. Adoption, as the dependent variable in the model, is measuring the extent to which BI systems have diffused across organisational activities or processes (Liang et al., 2007). This concept of diffusion has been widely used as a basis for conceptualizing IS adoption and use at the organisation level (Cooper and Zmud, 1990; Rogers, 1965; Zmud and Apple, 1992). The significant paths are indicated in one header arrows, while the paths not significant are indicated on dotted one header arrows. The final indices suggest it was acceptable to proceed with examination of the “hypothesised relationships within the model”. Table 81 indicates the path coefficients of the “hypothesised relationships within the proposed research model”. Table 82 presents the R-squared coefficients for the dependent variables. It was found that the model explained 10.0% of the informal MCS variance (R^2) and 28.8% of sophistication of formal MCS variance (R^2). In addition, the model explained 25.1% of the financial performance variance. The full data also found that the variances (R^2) explained for customer performance, business process performance and feedback and learning were 15.2%, 19.4% and 22.2% respectively (see Table 82).

Table 81 The Results of Hypothesised Model

Hypothesis	**Path**	**Estimate**	**S.E.**	**C.R.**	**P**	**Supported**
Hb1a	NCR <--- AD	0.500	0.095	5.244	***	Yes
Hb1b	NBP <--- AD	0.360	0.115	3.129	0.002	Yes
Hb1c	NOL <--- AD	0.296	0.104	2.851	0.004	Yes
Hb2	FP <--- AD	0.257	0.118	2.172	0.03	Yes
Hb3	SIC <--- AD	0.308	0.071	4.362	***	Yes
Hb4	SFC <--- AD	0.616	0.079	7.792	***	Yes
Hb5a	NCR <--- SFC	0.168	0.076	2.223	0.026	Yes
Hb5b	NBP <--- SFC	0.185	0,091	2.021	0.043	Yes
Hb5c	NOL <--- SFC	0.264	0.082	3.204	0.001	Yes
Hb6	FP <--- SFC	0.014	0.089	0.16	0.873	No
Hb7a	NCR <--- SIC	0.030	0.085	0.35	0.726	No
Hb7b	NBP <--- SIC	0.222	0.102	2.165	0.03	Yes
Hb7c	NOL <--- SIC	0.229	0.092	2.481	0.013	Yes
Hb8	FP <--- SIC	-0.077	0.098	-0.784	0.433	No
Hb9a	FP <---NCR	0.374	0.081	4.63	***	Yes
Hb9b	FP <--- NBP	0.142	0.069	2.06	0.039	Yes
Hb9c	FP <--- NOL	-0.013	0.076	-0.17	0.865	No
Control variable 1	NBP <--- OE	0.342	0.115	2.966	0.003	Yes
Control variable 2	NCR <--- OE	0.207	0.092	2.263	0.024	Yes
Control variable 3	NBP <--- ST	0.144	0.075	1.936	0.053	Yes
Control variable 4	NOL <--- OS	0.266	0.094	2.834	0.005	Yes
Control variable 5	NOL <--- QB	0.222	0.07	3.158	0.002	Yes
Control variable 6	FP <--- ST	0.195	0.068	2.848	0.004	Yes

Hypothesis	Path	Estimate	S.E.	C.R.	P	Supported
NCP= Customer performance; NBP=Business process performance; NOL= Feedback Learning and development; AD=Adoption of BI system; FP=Financial performance; SIC=Informal controls; SFC=Formal controls; OE=Organisational environment; ST= Strategy; OS=Organisational structure; QB=Quality of the board						

Table 82 R-squared Results

Variables	Estimate
SIC	0.100
SFC	0.288
NCR	0.152
NBP	0.194
NOL	0.222
FP	0.251

As presented in Table 81, 13 out of 17 hypotheses were directly supported by the model tested, with four hypothesized paths not supported. The adoption of BI was found to have a significant positive influence on customer ($p<0.001$), business process ($p<0.01$), organisational feedback and learning ($p<0.01$) performance. These supports Hb1a, Hb1b and Hb1c. This confirms that the adoption of BI systems improves the "non-financial performance" of firms. In addition, the adoption of BI systems was found to have a positive significant influence on financial performance ($p<0.05$). This supports Hb2. The adoption of BI systems thus has a direct influence on financial performance. In addition, the adoption of BI systems has a positive significant influence on sophistication of formal ($p<0.001$) and informal ($p<0.001$) controls. This supports Hb3 and Hb4. This means that the adoption of BI systems plays a critical role in improving formal and informal controls.

In turn, the sophistication of informal controls has positive significant influence on business process performance ($p<0.05$) and feedback and learning performance ($p<0.05$). This supports Hb7b and Hb7c. This confirms that the sophistication of informal controls improves business process and feedback and learning performance. However, sophistication of informal control has no significant influence on customer performance ($p>0.05$) and financial performance ($p>0.05$). These reject Hb7a and Hb8. The improvement of financial performance by informal management accounting controls occurs through the improvement of non-financial performance, such as business processes first. This is somewhat surprising given the purpose of MCS and is discussed further below.

The sophistication of formal controls has a positive significance influence on customer performance ($p<0.05$), business process performance ($p<0.05$), and feedback and learning performance ($p<0.001$). This confirms that the sophistication of formal controls improves non-financial performance. These support Hb5a, Hb5b and Hb5c. In addition, the sophistication of formal controls has no direct significance influence on financial performance ($p>0.05$), leading to the rejection of Hb6. The extensive use of formal controls does not directly improve the financial performance of the organisation and, as was the case with informal controls, exerts its influence through non-financial performance outcomes.

The improvement in "customer performance" ($p<0.001$) and "business process performance" ($p<0.05$) has a positive significant influence on the financial performance. These support Hb9a and Hb9b. This confirms that improvement of customer performance and business processes can improve financial performance more than feedback learning and development. Sophistication of informal and formal controls alone have no direct impact on financial performance. Moreover, organisational feedback and learning performance improvement ($p>0.05$) has no significance influence on financial performance. This rejects Hb9c. Overall, the role of feedback learning and development in the balanced scorecard is not well supported and needs to be further considered in future work.

The model hypothesised that the adoption of BI systems has a direct influence on financial performance. It was found that BI usage exerts a direct influence on financial performance, as well as an indirect influence through control systems and non-financial performance. These effects may occur because the adoption of BI systems can eliminate errors in operations, such as in product price setting (Nespeca and Chiucchi, 2018), and it can improve revenue because the price of products can be more accurately determined (O'Brien and Kok, 2006; Pirttimäki et al., 2006). BI systems contribute to economies of scale as organisations can avoid additional headcounts, saving on operating and general administration expenses (Petrini and Pozzebon, 2009). Velcu (2007) also suggests adoption of BI systems may result in organisations being able to reduce IT infrastructure costs. The impact of BI on cost reduction can also occur initially through non-financial indicators, particularly optimisation of business process (Kubina et al., 2015).

Control variables (quality of the board, organisational environment, strategy, and organisational structure) were introduced to control for their possible confounding effects on financial and non-financial performance outcomes (customer performance, business process performance and feedback and learning performance), and thus to better isolate the effects of the sophistication of formal and informal MCS controls and BI system adoption. Figure 36 identifies the quality of the board, organisational environment, strategy, and organisational structure as each having significant effects on various financial or non-financial performance outcomes, respectively. The paths that were non-significant were dropped during the initial testing of the model to improve model fit. The results of the hypothesis tests are further discussed next.

8.3 Discussion

Organisations have various issues that need to be resolved relating to the adoption of BI systems. In addressing these concerns, there is a need for organisations to understand the impacts of adoption of BI systems on a balanced set of organisational performance measures, both directly and indirectly, through impacts on the sophistication of management control systems. This chapter identified and empirically examined the extent to which the organisational adoption of BI systems impacts on a balanced set of organisational performance measures. both directly and indirectly, through impacts on the sophistication of management control systems (RQ3). To do so, a BI systems success model was developed and empirically tested. This was addressed by drawing *inter alia* on the Balanced Scorecard (BSC) performance measurement system. The MCS control factors were also included (Chenhall, 2003). Data was collected from executives representing their organisations in South Africa. The study was aimed at extending the conceptualisation of organisational outcomes – including the sophistication of MCS and a balanced set of organisational performance measures and obtaining the South African organisational perspective on BI systems adoption success. The AMOS test results presented in Figure 36 and Table 81 indicate that the "adoption of BI systems have an impact on organisational outcomes", "both directly and indirectly", through improving the sophistication of management controls.

"Adoption of BI systems" was found to have significant influence on the sophistication of informal controls. The study found that the adoption of BI systems improves the sophistication of informal controls such as decision making, open communication, information sharing and adaptation. The sophistication of informal control in turn, improves the non-financial performance. The hypothesis tested indicates that not all aspects of non-financial performance were however, improved. The customer performance outcome is not improved by the sophistication of informal controls. However, the adoption of the BI system directly improves the customer performance. This is a new contribution as Kallunki et al. (2011) measured non-financial performance as a single construct instead of distinguishing between “customer performance”, “business process performance and feedback and learning performance”. The study indicates that not all constructs of non-financial performance are affected by the sophistication of informal controls. This is because informal controls focus on the organisational internal environment without looking at customer performance. Customer performance can only be measured after the products or services have been sold. The adoption of BI systems, however, allows for data on customer relations to be collected and analysed so that customer performance outcomes can be improved, hence adoption of BI systems can directly improve this non-financial performance outcome (Petrini and Pozzebon, 2009; Hadid and Al-sayed, 2021). BI systems help an organisation to better identify promotions that customers are reacting too. This allows for reallocation of the marketing budget to successful campaigns that may yield higher returns on investment (Lönnqvist and Pirttimäki, 2006; Popovič et al., 2018). BI systems allow organisations to be better focused on customer-based business improvement initiatives. Kallunki et al. (2011) stated that customer analytics initiatives from BI improved customer retention, enabled higher revenues from cross-sell campaigns, and improved levels of customer satisfaction.

Those organisations that have adopted BI systems to a greater extent, were found to have an improvement in the sophistication of formal controls. This study found that adoption of BI system improves the sophistication of formal controls, such as activity based costing, planning system, budgeting system, external auditing system, internal auditing system, production/service control and monitoring system. The sophistication of formal controls can subsequently improve non-financial performance (business process, customer performance and feedback learning and development). The model presented in Figure 36 illustrates that the data supported the hypothesis that improvement in non-financial performance occurs, in part, through the sophistication of formal controls. This is consistent with the findings by Elbashir et al. (2011). However, their study did not include various elements of non-financial performance, such as business process performance, customer performance and feedback learning and development. Sophistication of formal controls requires that the organisation re-engineer the current business processes in line with the BI system requirements (Elbashir et al., 2021). Moreover, BI systems improve sophistication of formal controls by encouraging better planning and monitoring the implementation of the strategic goals. In this way, BI systems can fulfil the demand of many management controllers for remote and prompt control with real-time information monitoring of achievements toward organisational targets (Chapman and Kihn, 2009; Peters et al., 2016). In addition, a BI system can provide information on the extent to which the revenue, marketing, production or service and expenditure budgets are met, and can make this information visible to all the employees within the organisation (Chapman, 2005; Granlund and Mouritsen, 2003; Liew, 2019). Such visibility of information can encourage employees to work towards achieving the target without requiring active management oversight to direct them to do so (Granlund, 2011; Quattrone and Hopper, 2005; Paré et al., 2015). Furthermore, sophistication of formal controls strengthens the organisational internal control environment and improves segregation of duties, this can result in fewer audit findings from internal and external auditors (Granlund and Malmi, 2002; Felicio et al., 2021; Sutton, 2006).

Surprisingly, both the sophistication of formal and informal controls were found to have no direct statistically significant influence on financial performance. Therefore, hypothesis Hb6 and Hb8 are not supported. Improvement in financial performance occurs when an efficient MCS is built to improve business processes, customer satisfaction and feedback learning and development. MCS cannot directly affect financial performance as the controls are implemented to improve efficient monitoring and allocation of resources to the set objectives and goals of the organisation (Chenhall, 2006; Peters et al., 2016).

Informal controls are used to manage the behaviour of employees in achieving the organisational objectives (Chenhall, 2003), such as through informal communication and participation in decision making. This may help drive the intermediary outcomes but do not directly lead to financial performance improvement. Unexpectedly, informal controls appear not to influence customer performance. Informal control appears to mostly influence the behaviour of the employees in operational processes, such as to produce a better quality of product (Wu and Chen, 2014). Informal controls can thus best be understood to influence performance primarily through a business process improvement dimension.

Formal controls deal with the allocation and monitoring of resources such as using a "costing system", "budgeting system", "performance management system", "cost control system and auditing system" (Granlund, 2011). The formal controls systems also contribute to the re-engineering of business processes, improved customer performance and employee feedback learning and development. A sound control system helps managers to identify mistakes and correct mistakes before they become serious (Chapman and Kihn, 2009). This can aid an organisation to identify possible wastage in a process and direct the resources to the appropriate process to better achieve the set goals and objectives. MCS improvements are thus focused on lowering operational costs, improving efficiencies, reducing errors and rework, which then later translate to improvements in financial performance indicators, such as profitability (Hou, 2015). In addition, improved customer performance results in customer loyalty, return/repeat sales and potentially higher order volumes which would also be positive for financial performance. Moreover, MCS enabled through BI helps sales and marketing campaigns to be better targeted to the appropriate market segment and to reduce marketing costs.

Thus, despite the expectations that MCS would directly improve financial performance, the study found that the sophistication of MCS indirectly influences financial performance through improved non-financial performance, primarily customer performance and business processes, and the improvements in these non-financial performance outcomes then leads to future financial performance (Elbashir et al., 2021). In other words, the link between financial performance and sophistication of MCS appears to be mediated through certain non-financial performance outcomes. Moreover, this study confirms that formal and informal controls have independent effects on the performance outcomes and that they should not be considered substitutes (Kreutzer et al., 2016).

Feedback learning and development has a non-significant negative relationship with improvement in financial performance. This was not expected as it was hypothesised that better feedback learning and development would improve financial performance (Caseiro and Coelho, 2019). In addition, organisations that neglect training and development of their staff may have poor employee satisfaction (Hart and Snaddon, 2014). Organisations should invest in feedback learning and development to improve employees' skills and allow for proper testing of new ideas or products to improve financial performance (Božič and Dimovski, 2019). More attention must be paid to understanding how feedback learning and development translate to financial performance. One theory that may be useful here is Heskett's service-profit chain where the financial performance of firms is largely driven by customer service outcomes, such as customer satisfaction and loyalty. Customer service outcomes are in turn, influenced by satisfied, competent and committed employees who operate within the service delivery system (Heskett et al., 1994). See, for example, Cohen and Olsen (2013). That theory might then suggest that feedback learning and development improves employee outcomes which translate to improved process and customer service performance which in turn, translates to improved financial performance. Future work might consider modelling such effects.

Overall, these results have contributed by showing that aggregating the constructs of non-financial performance obscures their individual roles and effects on financial performance. This study has overcome such limitations by modelling performance constructs individually.

Adoption of BI systems was found to have a direct positive correlation with both financial and non-financial performance. Table 62 indicates that 81.5% of companies are performing 76-100% of their work through the BI system. Prior studies (Elbashir et al., 2008; Elbashir and Williams, 2007) examining the impacts of BI systems on non-financial performance only focused on internal business process improvement and ignored other aspects, such as organisational feedback learning and development, and customer satisfaction. The findings of this study confirm that adoption of BI systems improves "customer performance", "business process performance and feedback learning and development performance".

Once the BI systems are adopted, they help the employees to monitor the launch of a new product, create value for customers and improve efficiency. The study supported the significant relationship between the adoption of BI systems and feedback learning and development. The continuous use of BI systems assists South African organisations in improving their efficiencies and knowledge of the products launched. BI systems allow organisations to be able to identify and monitor key competencies required, such as cycle time, quality, employee skills and productivity. Monitoring the key competencies lead to prioritising key business processes to be focused on maximising shareholder value and customer satisfaction. In addition, Elbashir, Collier and Davern (2008) mentioned that BI systems help organisations in analysing their business processes to allow faster decision making on questions about re-engineering their business processes. This study supports those contentions. BI systems allow the monitoring of business process and customer performance, giving management an opportunity to continuously improve their business processes and staff productivities, lead times, service levels, cost, and quality (Hou, 2015; Aydiner et al., 2019). BI systems assist organisations to respond to customer concerns on time, while improving customer satisfaction, customer retention and consequently, increased market share. The findings are consistent with other prior studies (Lee, Park and Lim, 2013; Hou, 2015; Wu and Chen, 2014; Paré et al., 2020).

By extending the study of BI impacts to include not only business process but also customer performance and feedback learning and development performance, this study has provided a more holistic picture of the impacts of BI systems on non-financial performance. This is supported through Hb1a, Hb1b and Hb1c. Furthermore, the adoption of BI systems improves financial performance. This means that BI systems improve financial performance such as return on assets, operating income, sales growth, return on investment and operating costs. This is supported through Hb2. The study supports the results of previous studies (O'Brien and Kok, 2006; William and Williams, 2007) suggesting the adoption of BI systems can improve financial performance. Adoption of BI systems allows an organisation to monitor spending and reduce unnecessary costs that might not add value to the day-to-day running of the business. The reduction of costs may then improve the profitability, as the organisation is able to control the outflow of cash. Puklavec, Oliveira and Popovic (2014) argued that the intense use of BI systems may reduce cost, improve revenue, increase customer satisfaction, and market share. This study indicates that usage of BI systems in operational functions such as marketing, financial management, sales, human resources, supply chain and customer relations is associated with improved financial and non-financial performance. Importantly, these effects occur both indirectly through MCS and directly. Thus, there are other mechanisms through which BI influences performance not accounted for in the model. For example, Torres et al. (2018) suggest the dynamic capabilities perspective may offer one additional explanation.

Taken together, the findings provide an understanding of BI adoption and organisational performance, highlight the importance of distinguishing non-financial and financial performance outcomes, and the need to consider intermediary outcomes, such as sophistication of MCS, that support the translation of BI into improved performance outcomes.

The effect of control variables, such as organisational strategy, size, environment, structure, quality of board, on organisational outcomes is briefly discussed next.

8.3.1 Control Variables

The control variables were included in the model indicated in Figure 36. The following control variables were used: size, structure, strategy, environment, and the quality of the board. The control variables are used to ensure a better assessment of the hypothesised BI adoption and MCS latent variable's contributions to explaining the variance in organisational performance outcomes. A significant influence was found in some of the paths of the control variables, while other paths were not significant. The organisation size was measured using sales and number of employees. It has emerged that size has no effect on perceived improvements in financial and non-financial performance. Organisational environment has appeared to shape the improvement of business processes and customer performance with organisations operating in more dynamic and fast changing environments generally satisfied with their performance. Strategy focused on product/service innovation and cost controls appeared to have a high likelihood of improving customer performance. Furthermore, strategy has a significant impact on future financial performance. The structural arrangements of the organisation when focused on employee autonomy, emerged as having high likelihood of encouraging feedback and learning in the organisation. Strong oversight of the board was also found important to feedback learning and development outcomes. Even after the effects of these controls on the above factors was considered by the model, the adoption of BI remained significant for performance outcomes. This suggests BI systems extend the performance effects of other factors such as environment, organisational strategy, and structure, which are generally considered the primary determinants of performance outcomes.

8.4 Conclusion

This chapter presented the detailed interpretation of the key findings of the structural model hypothesizing the effects of the organisational adoption of BI systems. Adoption of BI was defined with reference to the extent to which the BI systems have diffused across organisational activities or processes (Liang et al., 2007). The model tested examined the relationships between the exogenous (adoption of BI) and endogenous latent constructs (sophistication of informal controls, sophistication of formal controls, non-financial performance, and financial performance). More specifically, the organisational impact of the adoption of BI was examined for effects on a balanced set of organisational performance measures, both directly and indirectly, through impacts on the sophistication of management control systems. The selection of performance outcomes was influenced by the BSC framework of Kaplan and Norton (1992). The study reported in this chapter has contributed to the literature by adding non-financial performance to the measurement of BI system outcomes. In addition, every element of non-financial performance was measured separately instead of aggregating them. The study extended on the work of Vakalfotis et al. (2011) by expanding on non-financial performance as customer performance, business process performance and feedback and feedback learning and development. Vakalfotis et al. (2011) argued that adoption of information systems does not improve non-financial performance, without specifying which elements of non-financial performance are not improved. This study however confirms that the adoption of BI systems directly assists in improving non-financial performance (customer performance, business process performance and feedback learning and development). Furthermore, support was found for the hypothesis that the adoption of BI systems directly improves the financial performance of organisations. This assisted to confirm previous results (O'Brien and Kok, 2006; Williams and Williams, 2007; Chapman, 2005) by providing evidence on the impact of the adoption of BI system on financial performance. This chapter thus provides evidence that the adoption of BI systems improves the balanced set of performance measures. This is important for management to better justify investments into BI systems within their organisations.

Further, the study provides evidence on the impact that the adoption of BI systems has on the sophistication of MCS and demonstrated how MCS improves non-financial performance. However, the study did not find that sophistication of formal and informal MCS controls improves financial performance directly. Rather, MCS influences non-financial performance, particularly customer performance and business process, which then improves future financial performance. Vakalfotis et al. (2011) and Chapman and Kihn (2009) argued that formal controls help to achieve better organisational performance. This study extended their work and found that the balance between sophistication of formal and informal controls helps to improve non-financial and consequently, financial performance. The findings of this study indicate that sophistication of informal and formal controls improves non-financial performance, which then improves financial performance. The findings of this study corroborate previous (Chenhall, 2006; Hart and Snaddon, 2014; Malmi and Brown, 2008) evidence which encourages the use of MCS. The chapter further contributed by demonstrating that improvements in MCS can be achieved through the adoption of BI systems. BI systems help formal controls by, for example, automating budgeting in the BI system, and informal controls by improving information sharing and participation in decision making. In Chapter 9, the thesis is concluded.

CHAPTER 9: CONCLUSION AND RECOMMENDATIONS

9.1 Introduction

The previous chapters (chapter 6, 7 and 8) validated the BI success model from the individual and organisational perspectives. This chapter provides the conclusions of the research findings. The chapter initially provides the overall summary of this research and thereafter, indicates the research contributions of the study which include theoretical, contextual, methodological, and practical contributions. In addition, the research limitations and the direction of future studies is also discussed. The last section provides an overall conclusion of the thesis.

9.2 Summary of the Study

In chapter 1, the study introduced research problems and the motivation of conducting the study. The study investigated two research problems. The first problem of the study was to investigate the factors influencing the innovative use of BI systems by individuals in the management accounting context. There was also a need to further investigate the impacts of innovative use of BI systems on management accountants' individual performance. However, it has been revealed that prior studies have not distinguished between routine and innovative use. This has resulted in factors influencing innovative use not being well understood. The second problem investigated is whether BI systems have impacts on organisational outcomes – including the sophistication of MCS and a balanced set of organisational performance measures. The focus on measuring performance only in terms of financial performance is not sufficient, there is a need for inclusion of both financial and non-financial performance to provide a balanced view on performance outcomes. In addressing the two research problems three research questions were posed namely RQ1[20], RQ2[21] and RQ3[22].

In chapter 2, through the literature review, the study introduced BI systems and their components, discussed the evolution of BI systems from earlier management information and decision support systems and identified some use cases for BI systems in support of operational, tactical, and strategic decision making. The potential benefits of BI systems were deliberated, along with various challenges and shortcomings. The review highlighted that the

[20] RQ1: "What are the factors influencing the extent of innovative use of BI system among management accountants"?

[21] RQ2: "What is the impact of innovative use of BI system on the individual performance of management accountants"?

[22] RQ3: "To what extent is the organisational use of BI systems impacts on a balanced set of organisational performance measures both directly and indirectly through impacts on the sophistication of management control systems"?

realisation of benefits is likely to be dependent on BI system use and that benefits are often difficult to quantify. Finally, the chapter presented a discussion on the use of BI systems, specifically in the management accounting context. Prior research had provided a limited understanding of BI system use by management accountants, and it was important for this study to extend understanding of how individual management accountants interact with BI systems and what factors affect their use of these BI systems. Furthermore, the relative complexity of management accountants' tasks may encourage different types of use along with different levels of satisfaction with BI systems. The literature review demonstrated that additional evidence was needed on whether the use of BI systems would enhance management accounting functions and their individual performance. Furthermore, the literature review assisted to motivate the importance of research into BI adoption and impacts at the organisational level with a need to examine the effects on financial and non-financial performance along with indirect effects through management control systems. The results of such an investigation would contribute much needed evidence for organisations to justify their investments in BI systems. It therefore emerged from the literature review that studies into BI use at the individual level of the management accountant was warranted, along with a study of BI impacts at the organisational level.

Chapter 3 focused attention on BI use at the individual level and introduced and explained an extended D&M model as a theoretical underpinning. This chapter thus addressed research objectives (RO1 and RO2) which were to identify and empirically examine factors explaining observed variation in the use of BI systems and the impact of use on individual-level performance of management accountants. Importantly, a distinction was made between routine and innovative use of BI systems. This chapter then developed a research model predicting the effects of innovative use on individual performance. The model represents several extensions over the original D&M model. It has included data quality, distinguished between routine use and innovative use, and considered the moderating effect of task complexity. Moreover, the chapter addresses the limitations of past studies to address causal ordering between use, user satisfaction and individual user performance by hypothesizing a set of cross-lagged models. There was a need to understand if the innovative use of BI systems can improve the individual job performance of management accountants over time. This forms part of the bigger issue to justify the investment made on BI systems from a South African context. This study has developed an extended D&M IS model of the factors influencing innovative use of BI systems and the subsequent impacts on performance.

In addition to the individual level, research on the impact of BI systems on organisational performance is still surfacing. In chapter 4, the BSC approach was adopted and discussed with the inclusion of the sophistication of formal and informal MCS. This chapter developed a research model that proposed addressing research objective (RO3) and research question (RQ3), specifically, to identify the impact of BI systems on the sophistication of MCS as well as on a balanced set of organisational performance outcomes (financial and non-financial performance). The work of Kallunki et al. (2011) provided the theoretical basis for the research model. The study thus addressed the second research problem focused on the impact that the adoption of BI systems has on a balanced set of organisational performance outcomes. Prior research had focused mainly on financial performance without considering non-financial performance. Moreover, in the context of management accounting, one intermediary performance outcome of significance, which may help explain the link between BI and organisational performance, is the performance of the MCS system. The implementation of BI systems was expected to result in improved sophistication of formal and informal MCS. Proper execution of MCS may subsequently result in the improvement of the organisational performance. MCS was thus hypothesised as an intermediary mechanism linking BI systems to organisational performance.

In chapter 5, the research methodology that was followed in order to test the individual and organisational level research models was presented and discussed. For both the individual and organisational level studies of the BI system, the research was informed by a positivist perspective and followed a quantitative deductive approach to hypothesis testing. The individual level study collected data through surveys of individual management accountants over three waves. The data collected from wave 1 was used for a cross-sectional test of the complete research model of the use and impact of BI systems on individual management accountants. Subsequent waves were used to test the cross-lagged effect models. The organisational level research model was tested using data collected via a cross-sectional survey of key organisational informants. All constructs in the research models were measured using multi-item scales that were subjected to tests of validity and reliability. The models were tested using SEM techniques. The data was analysed using statistical software, SPSS AMOS version 25.

In chapter 6, the cross-sectional data was used to test the individual model developed to understand the factors influencing the innovative use of the BI system and its implications for individual performance of management accountants in the South African context. This chapter presented the detailed interpretation of the key findings of the structural model on individual use of the BI system to provide an answer to RQ1 and RQ2. The chapter found, through analysis of responses, that the factors influencing the innovative use of the BI system are system quality, data quality, information quality and service quality, along with self-efficacy and task complexity. The chapter has also distinguished routine use from innovative use and determined that routine use is less likely under condition of task complexity and does not rely on self-efficacy to the same extent as innovative use. The attributes of system quality, data quality, information quality and service quality are nonetheless important factors that also influence the routine use of BI systems. The chapter has also addressed the question of the impact of innovative use of BI systems, over and above routine use, on individual performance of management accountants. Results indicate that innovative use is significant for individual performance, such as for improving productivity and decision-making effectiveness. Innovative use is the critical element of supporting the management accountants in their job performance and quality of decision making. This study found that without innovative use of the features of BI systems, individual performance and quality of decision making cannot be achieved. For individual management accountants to achieve job performance and decision making, they need to use the advanced features of their BI system. If users are unable to use the advanced features of the BI system, they would normally be using the system routinely in supporting their work. Routine use contributes less to individual performance and quality of decision making as compared to the innovative use of BI.

Further, the chapter has extended the D&M IS success model by considering the different information needs of users. These differences in information needs arise from variations in the task complexity of the user. Users facing fewer complex tasks only need routine features and functions, while users facing more complex tasks will rely on more innovative features in their BI usage. Innovative features will assist with finding solutions to more complex decision problems, while the routine functions will not. Self-efficacy was also introduced as an additional determinant variable in the model influencing routine and innovative use. It was empirically supported that individual management accountants who have higher self-efficacy are more likely to use the innovative features of BI systems in performing their task. Thus, the innovative use of BI system features has been confirmed as a function of system attributes (system, data, information, and service quality), individual user attributes (self-efficacy), and characteristics of the management accountant's job (task complexity).

Chapter 7 focused on understanding the causal relationships amongst routine use, innovative use, user satisfaction and individual performance. Specifically, this chapter focused on the cross-lagged effects of BI system use, user satisfaction and individual performance of management accountants. Examining these effects was achieved by establishing temporal precedence by collecting and analysing data over three times waves. This chapter presented the detailed interpretation of the key findings of the cross-lagged models of individual use and provided an answer for RQ2. The chapter found, through analysis of responses, that early-stage innovative use of BI improves later-stage individual performance. Results also showed that early-stage user satisfaction is significant for subsequent individual performance, such as improving productivity and decision-making effectiveness, while those who use routine features may not improve productivity and decision-making effectiveness over time. These findings justify the differentiation between various types of use and help confirm the causal ordering of important IS success constructs that had received insufficient attention in prior work.

Finally, chapter 8 presented the detailed interpretation of the key findings of the structural model hypothesizing the effects of the organisational use of BI systems to provide an answer for RQ3. This study confirmed that the "adoption of BI systems" assists to improve directly "non-financial performance" ("customer performance", "business process performance and feedback and learning development"). This study found that both business process, customer performance and feedback and learning performance can be improved. Furthermore, support was found for the hypothesis that the adoption of BI systems directly improves the financial performance of organisations. The study also provided evidence on the impact that adoption of BI systems has on the sophistication of MCS, and that MCS improves non-financial performance. However, the study did not find that sophistication of formal and informal controls improves financial performance directly. Rather, MCS influences non-financial performance, particularly customer performance and business processes, which then improves future financial performance. Feedback learning and development performance was however found not to have an impact on the improvement of future financial performance. Overall, the role of feedback learning performance in the balanced scorecard needs to be further considered in future work. Nonetheless, the chapter confirmed that the organisational adoption of BI systems has statistically significant impacts on various organisational performance outcomes, both directly and indirectly, through impacts on management control systems.

9.3 Contributions of the Study

This thesis examined the use of BI systems at both the individual and organisational levels of analysis. This has enabled the thesis to make a number of theoretical, contextual, methodological, and practical contributions.

9.3.1 Theoretical Contributions

First, a theoretical contribution was made by drawing on and extending the D&M IS success model to develop a BI systems success model, focused on innovative use. The original D&M IS model considers information quality, system quality and service quality as factors influencing IS usage and user satisfaction. This study extended the D&M IS success model by including data quality as an additional attribute of specific relevance in a BI system environment. Moreover, given that the emphasis of a BI system is on gathering, managing, analysing, and sharing information about the external and internal environment to gain insights for better decision making, this study has contributed the constructs of data quality as an important dimension of BI system success. Data quality refers to data that is considered accurate and complete with existing data records never missing. The quality of data was found to be an essential system success factor in the BI context and found to have a significant influence on both the routine and innovative use of a BI system. The inclusion of data quality in the BI success model alongside information quality ensures that the model accounts for both the inputs (data quality) and outputs (information quality) of BI systems. Management accountants should focus on data quality as they are expected to provide reliable information to management for decision making. Failure to cleanse data may affect the effectiveness of the system and results in management accountants continuing to re-work data on standalone system such as excel, despite the investment made in BI implementations.

Another theoretical contribution of this study was the conceptual development and distinction between the constructs of routine and innovative use. The construct of innovative use has not been sufficiently explored. Previous studies (Delone and McLean, 2003; Wang et al., 2007; Chen, 2010; Hou, 2012) did not distinguish the type of use when measuring the BI success factors. Within the D&M IS success model, system use was typically conceptualised as a single unidimensional construct. There was a need to fully understand how individuals, such as management accountants, can utilise their BI systems to improve their individual performance. Routine use of basic features like prewritten reports was found to contribute less to individual performance and quality of decision making as compared to the innovative use of the BI system. Through initial qualitative interviews supplemented with literature, this thesis was able to conceptualise innovative use as involving users using advanced features of BI systems such as self-service tools, interactive visualization, predictive analytics, and drill down functionality to support their work and improve their individual performance. The results of the study have found that both routine use and innovative use are important to performance but that innovative use has a stronger path coefficient. By testing the model, the study determines the utility of the underlying theories in explaining the innovative use of BI systems and establishing innovative use as a prerequisite for individual user performance. Future research should continue to distinguish between the two types of use. More importantly, management accountants should use dashboard features of the BI system to report on key performance indicators of the organisation. This would make monitoring the achievement of targets easier on all managers and speed up decision making as information is readily accessible to all stakeholders within the organisation.

In addition, the concept of task complexity was introduced to moderate the effect of the links between use (innovative and routine use) and user performance. Task complexity was found to have no moderating effect on routine use but a significant positive moderating effect on innovative use. Use of the innovative features is required to find solutions to more complex decision problems. As task complexity increases, users shift from routine toward innovative use. Thus, this study has made an additional theoretical contribution by demonstrating that task complexity motivates innovative use of IS systems, and specifically BI systems in the case of management accounting practice. Management accountants should use innovative features of BI systems to perform their more complex management accounting functions including but not limited to budgeting, reporting, forecasting and product costing. In particular, advanced features such as predictive analytics, predictive modelling, statistical analytics, prescriptive analytics and performance metrics may be useful in these tasks.

It is imperative in IS success research that causal relationships using techniques such as cross-lagged models, be established to understand if early use of a system affects later-stage user performance, and whether user satisfaction changes over time and affects later-stage individual use and/or performance, along with any reciprocal effects. This study found that innovative use of a BI system improves individual performance over time. This study also found that user satisfaction with their BI system improves performance over time. Management accountants who enjoy the use of the BI system, subsequently perceive it as contributing to their productivity, effectiveness and quality of decision making. This new evidence improves our understanding of the causal relationships between innovative use, user satisfaction and individual performance, and is thus a further theoretical contribution made by this study.

This study went beyond the individual user level to also examine the impact of BI adoption at the organisational level. Further theoretical contributions were thus made. First, using the BSC approach, the study confirms that BI systems have effects on various measures of financial and non-financial performance. The constructs of non-financial and financial performance in a BI systems environment had not previously been sufficiently explored. Adoption of BI was found to directly improve both financial and non-financial performance. Furthermore, adoption of BI systems was found to have significance influence on the sophistication of informal controls, which were found to improve some elements of non-financial performance except for customer performance. Thus, this study was able to trace the performance impacts of BI adoption on performance directly and indirectly through effects on the management control systems of an organisation. Surprisingly, both the sophistication of formal and informal controls were found to have no direct statistically significant influence on financial performance. The adoption of BI systems may result in an improvement in financial performance only if it is built on top of an efficient MCS to improve business processes, customer satisfaction and feedback and learning. This is a new contribution as previous studies measured non-financial performance as a single item instead on expanding it to include customer, internal business processes and feedback learning and development. The study also considers the potential impact of organisation size, structure, strategy, environment, and the quality of the board on the links between BI systems and MCS and organisational performance. The testing of the model thus contributes to the development of theory that explains the mechanisms through which BI systems influence organisational performance and extends our understanding of the organisational conditions under which BI systems usage is most important to performance.

9.3.2 Contextual Contribution

The study made a contextual contribution by examining BI systems use at both the individual and organisational levels in the context of management accountants from the South African context. The study makes an extensive contribution to the field of accounting information systems through evaluating whether BI systems have impacted the sophistication of MCS in the organisation. The sophistication on formal and informal controls has been evaluated to provide guidelines to management accountants and business executives on how to deploy and use BI in an MCS environment to enhance controls within the organisation. For example, the BI system should be implemented in a way that it handles the planning and budgeting value chain in its entirety. It must not be used as a monitoring tool only, as lack of accurate planning and budgeting may defeat the purpose of implementing the BI system. The BI system provides information on planned targets and actual performance (Rauhamäki, 2014). The absence or inaccuracy of planning information on the BI system would impact negatively on the MCS. To strengthen the MCS, the BI system should also handle planning and budgeting (Granlund, 2011). This is due to the fact that the MCS encourages employees to implement organisational objectives using the information available on the BI system. Therefore, it is prudent that the BI system becomes the system that can also handle planning, due to the fact that historic data available on the BI system can be used to plan for the future. The use of any other system for planning would not leverage the amount of previous data already available on the BI system. In the context of South Africa, the study shows BI systems are being implemented in manufacturing, mining, utilities and energy, public sector, among other industries, and thus its diffusion across the industries is evident. The study has also provided evidence on the impact that the adoption of BI systems has on sophistication of MCS and on non-financial performance. This shows the relevance of outcomes such as customer performance and learning and development for South African organisations wanting to assess the impact of BI systems. This is important given the subsequent effects of non-financial performance outcomes on financial performance (see also Elbashir et al., 2021).

The study also found early use influences later-stage job performance and decision making. Furthermore, individual level performance improved through continued use of the advanced features of the BI system. The finding supports the work performed by Benlian (2015) who theorised that expanding the information technology features used over time may lead to performance improvement. Early-stage user satisfactions were found to contribute towards improvement of individual level performance over time.

Management accountants are expected to perform planning, budgeting, forecasting, costing, and reporting tasks. To perform these tasks, they can benefit from the innovative use of BI systems, such as through the use of predictive analytics features, sales demand can be predicted to make decisions on future customer sales or demand. This study has confirmed that management accountants who extend beyond routine and into innovative use are overall more satisfied with and continue to benefit from BI system implementations.

9.3.3 Methodological Contribution

The study has several methodological contributions. This includes but is not limited to how longitudinal designs and structural equation modelling (SEM) can be combined to improve our understanding of IS success.

SEM has become a popular statistical technique widely used to test theory in various fields (i.e., information system, management science). SEM is a multivariate statistical procedure that consolidates both multiple regression analysis and factor analysis in testing the hypothesised model, in order to establish causality within latent (or construct) and observed variables that form part of the model (Barrett, 2007; Sangthong, 2020). SEM provides for both a confirmatory test of the measurement model (relationship between each latent construct and its indicators) and a test of the structural model (relationships between the latent constructs themselves) (Hair et al., 2010). The use of these techniques in this study went beyond previous work in BI systems' use research. This study is one of the few studies that used SEM to test the cross-lagged causal relationships between use, user satisfaction and individual performance. This provides an example on how AMOS and SEM can be applied in an IS use and performance research as a technique for analysis.

The study contributes by using a novel technique (SEM cross-lagged model) to shed light on an important question regarding the causal connection between use, user satisfaction and individual performance. In IS research, there are few studies that used cross-lagged SEM design. This is important to guide future research how to model use, user satisfaction and performance relationships in a BI-system context. An important question about causality within the field has now been better examined. This study has indicated the advantages of using the method. The approach adopted in this study is useful to provide guidance to future IS researchers on how to use a cross-lagged design to study the causality phenomenon. The use of the cross-lagged SEM design in this work can help guide future researchers.

The study makes additional methodological contributions by having operationalised measures of innovative use, routine use that is informed by the literature as well as an initial round of interviews with BI system users, and this resulted in an improved D&M IS success model. Further, the BSC approach resulted into the development and validation of a balanced set of performance measures of BI systems from the organisational point of view. The balanced performance measurement may assist future researchers and organisations in measuring the benefits and success of BI systems and could be adapted for other system contexts.

9.3.4 Practical Application

Fourth, the results of this study can assist organisations to improve decisions on how to invest in and deploy BI systems, as well as the types of interventions that may be needed to achieve innovative use by individuals.

The need to understand the dynamic nature of innovative use, user satisfaction and individual performance is of practical interest (Kjeldskov, Skov and Stage, 2010). The results of this study provide organisations with a better understanding and justification for investments in the implementation of the BI systems and for better management of system use over time.

The results of the study found that both routine use and innovative use are important to performance but that innovative use has a stronger path coefficient and future research should continue to distinguish between the two. This has implications for how practice should train users on the two types of use separately. Self-efficacy was important to innovative use and this can be improved through training. Moreover, organisations should pay attention to and find ways to encourage more innovative use by manipulating system quality, data quality, service quality and information quality as these were found to be important factors of innovative use. Moreover, early-stage perceptions are important as they have implications for downstream use and performance outcomes. So, ensuring early-stage user satisfaction through IS attributes is important as perceptions are sticky and possibly difficult to recover in later-stages. For example, organisations could ensure they design the format of information outputs, to make them easier to understand and to be more consistent for users. This is important in ensuring BI satisfaction and system use as information might be useful for a particular task, but if it is not presented in a simplified way, it can become useless to the user (Laumer et al., 2017; Laumer et al., 2016).

Practitioners can also benefit from this study’s findings related to BI adoption at the organisation level. The balanced performance measurement assists practitioners and organisations in measuring the benefits of implementing BI systems.

9.4 Limitations

The study has several limitations which must be acknowledged. Firstly, data at the organisational level was collected using a single cross-sectional survey, which introduces significant limitations in the ability to establish temporal precedence in the data and to make causal inferences (Collis and Hussey, 2009). Therefore, in answering RQ3 regarding the effects of BI systems on organisational performance and MCS, common method biases may exist as responses represent perceptions at a single point in time. Secondly, common methods bias also arises as data on all variables was collected from a single respondent (Lee and Lings, 2008). Causal inferences can thus be made only with reference to the theoretical reasoning presented in the literature and model development chapters.

In the study of individuals, however, data was collected over three waves (period). This reduced threats to causal inference. Moreover, by collecting repeated measures at the different waves, the autocorrelation can be controlled, and cross-lagged effects estimated to strengthen causal inference. Thirdly, nonetheless, as with all survey studies, limitations arise with respect to response biases such as social desirability bias, as well as self-selection bias, amongst others (Lee and Lings, 2008; Byrne, 2013). Fourthly, due to time constraints, some respondents may have been unavailable at the time. Fifth, surveys measure the perception of the behaviour of the respondents, not the actual behaviour. The study only collected data based on the perception of the respondents, actual data for constructs of financial performance was not used. However, data such as income statement data often has its own limitations as it is subjected to accounting practices, irregularities and write-offs that might skew financial performance measurement. Moreover, data on other constructs modelled in this study are not typically available from financial reports. Sixth, for this study's examination of individual BI usage, data was collected over three-time waves. Although there is no general agreement in the literature on the most acceptable period between waves, the time period of 12 to 16 weeks used in this longitudinal study may be regarded as a short period for an information technology innovation to make an impact on its users. Thus, causal inferences from the observed associations still rely on theory. Future research may wish to consider different time periods. And finally, attrition of individuals across the three-time waves along with a potential non-response bias in the surveys is also a threat to external validity, where the people and organisations that respond are systematically different from those that did not respond. This constitutes a threat to the external validity of the findings as results may be less generalizable (Byrne, 2013).

9.5 Recommendations for Future Research

Future research should continue to distinguish routine and innovative use in the study of IS success, and to continue to explore why some users only use the routine features of an IS while other use more innovative features. This study found that system attributes and factors such as self-efficacy and task complexity are likely to be important, but others could also be explored. Further, this study confirmed that innovative use has a stronger influence on individual performance than routine use. There is a sense from the data that users start by using more routine features and at a later stage shift to innovative use. An opportunity of future studies to continue to explore how use changes over time and what additional factors, beyond those examined here, might increase innovative use after initial routine use. The type of the use is also important to the individual user's satisfaction. A decrease in usage can be an indication that the system is not performing the way it was intended and user satisfaction may be affected. Future study can investigate this impact (DeLone and McLean, 2003).

The study also did not measure user *dissatisfaction*. It might be observable that poor quality information outputs lead to dissatisfaction, but good quality information outputs do not necessarily lead to satisfaction. Future research could thus consider BI user satisfaction through the Kano model and differentiate IS attributes that are hygiene factors from those that have the potential to delight users in the BI context.

It was found that some early use behaviours are difficult to change and do not appear to reduce over time. In particular, the reciprocal relationship between early use and later user satisfaction. The relationship found between early innovative, routine use and later user satisfaction could guide future research to better model the two types of use. Innovative use was found to be stronger in supporting user satisfaction and individual performance as compared with routine use in explaining early innovative use of BI system at three waves.

This study argued that good IS support teams have an impact on user satisfaction. However, complex systems, even if well supported by a responsive team, may not necessarily be found enjoyable to use. Even if users feel that the support team is interested in solving their problems and being responsive to their needs, they will not necessarily feel the system works the way they want it to. This type of affective response of users to enterprise systems, such as BI systems, needs further exploration in future research.

Not at all the study's hypotheses were supported. For example, this study found that information quality had no significant impact on user satisfaction. In addition, service quality was negatively related to satisfaction and task complexity has no direct impact on routine use. To further understand these findings, future research may wish to employ qualitative case study analysis to explore these dynamics of BI deployment in more depth.

Moreover, the results of the study suggest that more attention must be paid to understanding how feedback learning and development translates into financial performance. One theory that may be useful here is Heskett's service-profit chain where the financial performance of firms is largely driven by customer service outcomes, such as customer satisfaction and loyalty. Customer service outcomes are in turn, influenced by satisfied, competent and committed employees who operate within the service delivery system (Heskett et al., 1994). The theory might then suggest that feedback and learning improves employee outcomes which translate to improved process and customer service performance which in turn, translate to improved financial performance. Future work might consider modelling such effects.

9.6 Conclusions

This study has contributed an extended BI system success model, which was tested through cross-sectional and three wave panel data collected from management accountants in South Africa. The empirical results confirm that innovative use is more important to individual performance than routine use of BI. The study further contributes much needed evidence of the relationships between BI adoption and organisational performance outcomes. The results confirm that BI adoption into the functional areas of an organisation is associated with various financial and non-financial performance outcomes and has positive effects on formal and informal management control systems. As a result, organisations are better positioned to justify investments into BI systems and to improve how BI systems are used over time to improve both individual and organisational performance.

REFERENCES

Abdi, H. 2010. *Partial Least Squares Regression and Projection on Latent Structure Regression (PLS Regression).* Hobokken, NJ.: John Wiley & Sons.

Abdusalomova, N. B. 2019. Principles of Ties of Internal Control and Management Accounting Systems at the Enterprises of Black Metallurgy. *ISJ Theoretical & Applied Science*, 3(71): 385-391.

Abusweilem, M. A., & Abualoush, S. 2019. The Impact of Knowledge Management Process and Business Intelligence on Organisational Performance. *Management Science*, 9: 2143-2156.

Adam, F., & Pomerol, J. C. 2008. Developing Practical Decision Support Tools Using Dashboards of Information. *In Handbook on Decision Support Systems II*, Springer Berlin Heidelberg, 1:151-173.

Agolla, J. E., & Van Lill, J. B. 2013. Public Sector Innovation Drivers: A Process Model. *Journal of Social Science*, 34(2):165-176.

Ahuja, M.K., & Thatcher, J.B. 2005. Moving Beyond Intentions and Toward the Theory of Trying: Effects of Work Environment and Gender on Post-Adoption Information Technology Use. *MIS Quarterly*, 29(3): 427-459.

Ain, N., Vaia, G., DeLone, W. H., & Waheed, M. 2019. Two Decades of Research on Business Intelligence System Adoption, Utilization and Success: A Systematic Literature Review. *Decision Support Systems*, 125:1-13.

Aldholay, A., Isaac, O., Abdullah, Z., Abdulsalam, R., & Al-Shibami, A. H. 2018. An Extension of Delone and McLean IS Success Model with Self-Efficacy: Online Learning Usage in Yemen. *The International Journal of Information and Learning Technology*. [online], Available https://doi.org/10.1108/IJILT-11-2017-0116/ [Accessed 5th February 2021].

Al-Mashari, M. 2001. Enabling Process-Orientation through Enterprise Resource Planning Systems, *Business Process Management Journal*, 7(3): 165-170.

Alnoukari, M., & Hananao, A. 2017. Integration of business intelligence with corporate strategic management. *Journal of Intelligence Studies in Business*. 7 (2): 5-16.

Ameen, A., Al-Ali, D., Isaac, O., & Mohammed, F. 2020. Examining relationship between service quality, user satisfaction and performance impact in the context of smart government in UAE. *International Journal of Electrical and Computer Engineering*, 10(6): 6026-6033.

Angelina, R. J., Hermawan, A., & Suroso, A. I. 2019. Analyzing E-Commerce Success Using DeLone and McLean Model. *Journal of Information Systems Engineering and Business Intelligence*, 5(2): 156-162.

Anthony, R. 1965. *Planning and Control Systems: a Framework for Analysis*. Cambridge, MA.: Harvard University Graduate Business School of Business Administration

Arnott, A., Lizama, F., & Song, Y. 2017. Patterns of Business Intelligence Systems use in Organisations. *Decision Support Systems,* 97: 58-68.

Arnott, D., Jirachiefpattana, W., & O'Donnell, P. 2007. Executive Information Systems Development in an Emerging Economy. *Decision Support Systems*. 42(4):2078-2084.

Arnott, D. 2008. Success Factors for Data Warehouse and Business Intelligence Systems. *ACIS Proceedings*, 55-65.

Arnold, V. 2018. The Changing Technological Environment and the Future of Behavioural Research in Accounting. *Accounting and Finance*, 58: 315-339.

Association of Chartered Certified Accountants (ACCA). 2012. *The Changing Role of the CFO*. United Kingdom, London: The Association.

Ashrafi, A., Ravasan, A.Z., Peter Trkman, P., & Afshari, S. 2019. The Role of Business Analytics Capabilities in Bolstering Firms' Agility and Performance. *International Journal of Information Management*, 47: 1-15.

Appelbaum, D., Kogan, A., Vasarhelyi, M., & Yan, Z. 2017. Impact of Business Analytics and Enterprise Systems on Managerial Accounting. *International Journal of Accounting Information Systems*, 25:29-44

Avgerou, C. 2013. Social Mechanisms for Causal Explanation in Social Theory Based IS Research. *Journal of the Association for Information Systems*, 14(8): 399-419.

Awang, Z., Afthanorhan, A., & Asri, M.A.M. 2015. Parametric and Non-Parametric Approach in Structural Equation Modeling (SEM): The Application of Bootstrapping. *Modern Applied Science*, 9(9): 58-67.

Awang, Z., Afthanorhan, A., & Mamat, M. 2016. The Likert scale analysis using parametric based Structural Equation Modeling (SEM). *Comput Meth Soc Sci*, 4(1): 13-21.

Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim,S., & Delen, D. 2019. Business Analytics and Firm Performance: The Mediating Role of Business Process Performance. *Journal of Business Research*, 96: 228-237.

Azeroual, O., & Theel, H. 2018. The Effects of Using Business Intelligence Systems on an Excellence Management and Decision-Making Process by Start-Up Companies: A Case Study. *International Journal of Management Science and Business Administration*, 4(3): 30-40.

Azita, S.S. 2011. An Approach to Building and Implementation of Business Intelligence System in Exchange Stock Companies. *Australian Journal of Basic and Applied Sciences*, 5(6): 1491-1495.

Barrett, P. 2007. Structural Equation Modelling: Adjudging Model Fit. *Personality and Individual Differences*, 42: 815-824.

Bartlett, M. S. 1954. A Note on The Multiplying Factors for Various Chi Square Approximations. *Journal of Royal Statistical Society, 16*(B): 296-298.

Bedford, D., Malmi., T. & Sandelin, M. 2016. Management Control Effectiveness and Strategy: An Empirical Analysis of Packages and Systems. *Accounting, Organizations and Society*, 51:12-28.

Benlian, A. 2015. IT Feature Use over Time and its Impact on Individual Task Performance. *Journal of the Association for Information Systems*, 16(3):144-173.

Baumgartner, H., & Homburg, C. 1996. Applications of Structural Equation Modeling in Marketing and Consumer Research: A Review. *International Journal of Research in Marketing*, 13:139-161.

Beal, B. 2005. *Half of Data Warehouse Projects to Fail*. [online], Available http://searchcrm.techtarget.com/news/1066086/Report-Half-of-data-warehouse-projects-to-fail [Accessed 5th February 2017].

Bhimani, A., Horngren, C., Datar, S., & Foster, G. 2008. *Management and Cost Accounting*. Hemel Hempstead: Prentice Hall.

Bokhari, R.H. 2005. The Relationship Between System Usage and User Satisfaction: A Meta-analysis. *The Journal of Enterprise Information Management,* 18(2): 211-234.

Bonner, S.E. 1994. A Model of the Effects of Audit Task Complexity. *Accounting, Organisations and Society*, 19: 213-234.

Božič, K., & Dimovski, V. 2019. Business Intelligence and Analytics Use, Innovation Ambidexterity, and Firm Performance: A Dynamic Capabilities Perspective. *Journal of Strategic Information Systems*, 28: 101578

Božič, K., & Dimovski, V. 2020. The Relationship between Business Intelligence and Analytics Use and Organisational Absorptive Capacity: Applying the Delone & McLean Information Systems Success Model. *Economic & Business Review*, 22(2): 191-232.

Bringnall, S., & Ballantine, J. 2004. Strategic Enterprise Management Systems: New Directions for Research. *Management Accounting Research*, 15 (1): 225-240.

Burton-Jones, A., & Straub Jr, D. W. 2006. Reconceptualizing System Usage: An Approach and Empirical Test. *Information Systems Research,* 17(3): 228-246.

Byrne, B. M. 2013. *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming*. London: Routledge.

Campbell, D. J. 1988.Task Complexity: A Review and Analysis. *The Academy of Management Review,* 13, 40-52.

Carenys, J. 2012. Management Control Systems: A Historical Perspective. *International Journal of Economy Management and Social Sciences*, 1(1): 1-18.

Carstensen, H. V., & Bason, C. 2012. Powering Collaborative Policy Innovation: Can Innovation Labs Help? The Innovation Journal: *The Public Sector Innovation Journal*. 17(1): 1-26.

Caseiro, N., & Coelho, A. 2019. The Influence of Business Intelligence Capacity, Network Learning and Innovativeness on Start-ups Performance. *Journal of Innovation & Knowledge*, 4: 139-145.

Chapman, C. S. 2005. Not because they are new: developing the contribution of enterprise resource planning systems to management control research. *Accounting, Organisations and Society*, 30; 685-689.

Chapman, C. S., & Kihn, L. A. 2009. Information Systems Integration, Enabling Control and Performance. *Accounting, Organisations and Society*, 34: 151-169.

Chen, C. W. D., & Cheng, C.Y. J. 2009. Understanding Consumer Intention in Online Shopping: a Respecification and Validation of the DeLone and McLean model. *Behaviour & Information Technology*, 28(4): 335–345.

Chen, H. J. 2010. Linking Employees' E-learning System Use to their Overall Job Outcomes: An Empirical Study Based on the IS Success Model. *Computers & Education*, 55: 1628-1639.

Chen, Y., & Lin, Z. 2021. Business Intelligence Capabilities and Firm Performance: A Study in China. *International Journal of Information Management*, 57: 1-15.

Chenhall, R.H. 2003. Management Control Systems Design within its Organisational Context: Findings from Contingency-Based Research and Directions for Future. *Accounting, Organisation and Society*, 28: 127-168.

Chenhall, R.H. 2006. Theorizing Contingencies in Management Control Systems Research. *Handbook of Management Accounting Research*, 1: 163-205.

Cheung, G. W., & Rensvold, R. B. 2002. Evaluating Goodness-of-Fit Indexes for Testing Measurement Invariance. *Structural Equation Modeling*, 9(2): 233-255.

Chong, V.K., & Eggleton, I.R.C. 2003. The Decisions-Facilitating Role of Management Accounting Systems on Managerial Performance: The Influence of Locus of Control and Task Uncertainty. *Advances in Accounting*, 20: 165-197.

CIMA. 2008. *Improving Decision Making in Organisations*. United Kingdom, London: The Association.

CIMA. 2010. *Peter Simons on management accountants and business intelligence.* [Online], Available From:http://www.cimaglobal.com/Thought-leadership/Newsletters/Insight-e-magazine/Insight-2010/Insight-May-010/Transform-yourself-with-business-intelligence [Accessed 4th February 2015].

Cohen, L., Manion, L., & Morrison, K. R. B. 2007. *Research Methods in Education*. 6th Edition. London: Routledge.

Cohen, J.F., Coleman, E., & Kangethe, M.J. 2016. An Importance-Performance Analysis of Hospital Information System Attributes: A Nurses' Perspective. *International Journal of Medical Informatics*, 86: 82-90.

Cohen, J.F., & Olsen, K. 2013. The impacts of complementary information technology resources on the service-profit chain and competitive performance of South African hospitality firms. *International journal of hospitality management*, *34*, 245-254.

Collis, J., & Hussey, R. 2009. *Business Research: A Practical Guide for Undergraduate and Postgraduate students*. 3rd ed. New York: Palgrave Macmillan.

Côrte-Real, N., Ruivo, P., & Oliveira, T. 2020. Leveraging Internet of Things and Big Data Analytics Initiatives in European and American Firms: Is Data Quality a Way to Extract Business Value? *Information & Management*, 57: 1-16.

Cooper, R. B., & Zmud, R.W. 1990. Information Technology Implementation Research: A Technological Diffusion Approach. *Management Science*, 36 (2): 123-139.

Courtois, C., Montrieux, H., De Grove, F., Raes, A., De Marez, L., & Schellens, T. 2014. Student Acceptance of Tablet Devices in Secondary Education: A Three-Wave Longitudinal Cross-Lagged Case Study. *Computers in Human Behavior*, 35: 278-286.

Cox, C. 2010. *Balancing Decision Speed and Decision Quality: Assessing the Impact of Business Intelligence Systems in High Velocity Environments*. Faculty of the College of Business Administration, United States - California, TUI University, Ph.D.

Davis, S., & Albright, T. 2004. An Investigation of the Effect of Balanced Scorecard Implementation on Financial Performance. *Management Accounting Research*, 5(2): 135–153.

Dawson, L., & Van Belle, J. 2013. Critical Success Factors for Business Intelligence in the South African Financial Services Sector. *SA Journal of Information Management*, 5(1): 1-12.

Dechow, N., & Mouritsen, J. 2005. Enterprise Resource Planning Systems, Management Control and the Quest for Integration. *Accounting, Organisations and Society,* 30: 691-733.

DeLone, W.H., & McLean, E.R. 1992. Information systems success: The quest for the dependent variable. *Information Systems Research*, 3 (1): 60–95.

DeLone, W.H., & McLean, E.R. 2003. The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems*, 19 (4): 9-30.

Dehning, B., Richardson, V. J., & Zmud, R. W. 2003. The Value Relevance of Announcements of Transformational Information Technology Investments. *Mis Quarterly*, 637-656.

Dinter, B., Schieder, C., & Gluchowski, P. 2011. Towards a Life Cycle Oriented Business Intelligence Success Model. *AMCIS Proceedings.*

Di Vaio, A., Varriale, L., & Trujillo, L. 2019. Management Control Systems in Port Waste Management: Evidence from Italy. *Utilities Policy*, 56: 127-135.

Doll, W. J., & Torkzadeh, G. 1998. Developing a Multidimensional Measure of Systems Use in an Organisational Context. *Information and Management*, 33 (4):171-185.

Drake, K.D., & Martin, A. M. 2020. *The Dynamic Role of Earnings and Returns in the Executive Contracting Working Paper*. University of Illinois, Chicago.

Elbashir, M., & Williams, S. 2007. BI Impact: The assimilation of Business Intelligence into Core Business Processes. *Business Intelligence Journal*, 2 (4): 45-54.

Elbashir, M. Z., Collier, P. A., & Davern, M. J. 2008. Measuring the Effects of Business Intelligence Systems: The Relationship Between Business Process and Organisational Performance. *International Journal of Accounting Information Systems*, 9:135–153.

Elbashir, M. Z., Collier, P. A., Sutton, S.G., Davern, M.J., & Leech, S.A. 2013. Enhancing the Business Value of Business Intelligence: The Role of Shared Knowledge and Assimilation. *Journal of Information Systems*, 27 (2):87-105.

Elbashir, M. Z., Philip, A., Collier, P. A., & Sutton, S.G. 2011. The Role of Organisational Absorptive Capacity in Strategic Use of Business Intelligence to Support Integrated Management Control Systems. *The Accounting Review*, 86 (1):155-184.

Elbashir, M. Z., Sutton, S.G., Mahama, H., & Arnold, V. 2021. Unravelling the Integrated Information Systems and Management Control Paradox: Enhancing Dynamic Capability Through Business Intelligence. *Accounting & Finance*, 61: 1775-1814.

Evans, J.R. 2010. *Statistics, Data Analysis & Decision Modelling*. 4th ed. Upper Saddle River: Pearson Prentice Hall.

Fan, X., & Sivo, S. A. 2005. Sensitivity of Fit Indices to Misspecified Structural or Measurement Model Components: Rationale of Two-Index Strategy Revisited. *Structural Equation Modeling*, 12(3), 343-367.

Farzaneh, M., Isaai, M. T., Arasti, M. R., & Mehralian, G. 2018. A Framework for Developing Business Intelligence Systems: A Knowledge Perspective. *Management Research Review*, 41(12): 1358-1374.

Felício, T., Samagaio, A., & Rodrigues, R. 2021. Adoption of Management Control Systems and Performance in Public Sector Organisations. *Journal of Business Research,* 124: 593-602.

Field, A. 2009. *Discovering Statistics Using SPSS: Introducing Statistical Method.* 3rd edition. Thousand Oaks, CA: Sage Publications.

Financial Mail. 2016. *Top Companies*. Annual report. [Online], Available at:http://www.financialmail.co.za/ [Accessed 28 August 2016].

Fink, L., Yogev, N., & Even, A. 2017. Business Intelligence and Organisational Learning: An Empirical Investigation of Value Creation Processes. *Information & Management*, 54: 38-56.

Fornell, C., & Larcker, D.F. 1981. Evaluating Structural Equations with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1): 39-50.

Gaardboe, R., Nyvang, T., & Sandalgaard, N. 2017. Business Intelligence Success Applied to Healthcare Information Systems. *Procedia Computer Science,* 121:483-490.

Gaardboe, R., Sandalgaard, N., & Nyvang, T. 2017. An Assessment of Business Intelligence in Public Hospitals. *International Journal of Information Systems and Project Management*, *5*(4): 5-18.

Gardner, H. J., & Martin, M. A. 2007. Analyzing Ordinal Scales in Studies of Virtual Environments: Likert or Lump It! Presence. *Teleoperators and Virtual Environments*, 16(4): 439-446.

Gartner, 2012. Gartner Says Worldwide Business Intelligence, Analytics and Performance Management Software Market Surpassed the $12 Billion Mark in 2011. *Gartner Research*, [Online], Available at:<http://www.gartner.com/>[[Accessed 21 July 2014].

Gartner, 2015. Market Share Analysis: Business Intelligence and Analytics Software. *Gartner Research,* [Online], Available at:<http://www.gartner.com/>[[Accessed 21 August 2015].

Gauzelin, S., & Bentz, H. 2017. An Examination of the Impact of Business Intelligence Systems on Organisational Decision Making and Performance: The Case of France. *Journal of Intelligence Studies in Business,* 7 (2): 40-50.

Gavrea, C., Ilies, L., & Stegerean, R. 2011. Determinants of organisational performance: The case of Romania. *Management & Marketing, 6*, 285-300.

George, D., & Mallery, P. 2010. *SPSS for Windows Step by Step: A Simple Guide and Reference 17.0 Update.* 10th Edition, Boston: Pearson.

Georgopoulos, B. S., & Tannenbaum, A. S. 1957. A study of organisational effectiveness. *American Sociological Review, 22*: 534-540.

Gibson, M., Arnot, D., & Jagielska. 2004. Evaluating the Intangible Benefits of Business Intelligence: Review & Research Agenda. *Decision Support in an Uncertain and Complex World*, The IFIP TC8/WG8.3 International Conference.

Giustia, R., Manerbaa, D., Brunoa, G., & Tadei, R. 2019. Synchromodal Logistics: An Overview of Critical Success Factors, Enabling Technologies, and Open Research Issues. *Transportation Research*, 129: 92-110.

Gregor, S. 2006. The Nature of Theory in Information Systems, *MIS Quarterly*, 30(3): 611-642.

Gregor, S., & Hovorka, D. 2011. Causality: The Elephant in the Room in Information Systems Epistemology. in *Proceedings of the European Conference on Information Systems,* Helsinki, Finland.

Gelderman, M. 1998. The Relation Between User Satisfaction, Usage of Information Systems, and Performance. *Information & Management*, 34(1):11-18.

Gong, M., Xu, Y., & Yu, Y. 2004. An Enhanced Technology Acceptance Model for Web-Based Learning. *Journal of Information Systems Education*, 15(4): 365-374.

Gorla, N., Somers, T. M., & Wong, B. 2010. Organisational Impact of System Quality, Information Quality, and Service Quality. *Journal of Strategic Information Systems*, 19(1): 207-228.

Gonzales, R., & Wareham, J. 2019. Analysing the Impact of a Business Intelligence System and New Conceptualizations of System Use. *Journal of Economics, Finance and Administrative Science*, 48(24): 345-368.

Grover, V. 2019. Surviving and Thriving in the Evolving Digital Age: A Peek into the Future of IS Research and Practice. *The DATA BASE for Advances in Information Systems*, 50(1): 25-34.

Grabski, S.V., Leech, S.A., & Schmidt, P. J. 2011. A Future Agenda for Accounting Information Systems. *Journal of Information Systems*, 25(1): 37-78.

Granlund, M. 2011. Extending AIS Research to Management Accounting and Control Issues: A Research Note. *International Journal of Accounting Information Systems*, 12: 3-19.

Granlund, M., Mouritsen, J., & Vaassen, E. 2010. Call for Papers “On the Relations Between Modern IT, Decision Making and Management Control”. *International Journal of Accounting Information Systems*, 11(1): III–IV.

Granlund, M., & Mouritsen, J. 2003. Introduction: Problematizing the Relationship Between Management Control and Information Technology, *European Accounting Review*, 12 (1): 77-83.

Granlund, M., & Malmi, T. 2002. Moderate Impact of ERPS on Management Accounting: A Lag or Permanent Outcome. *Management Accounting Research*, 2002;13: 299-321.

Goodhue, D.L., & Thompson, R. L. 1995.Task-Technology Fit and Individual Performance. *MIS Quarterly*, 19(2): 213-236.

Gyampah, K. A., & Salam, A. F. 2004. An Extension of The Technology Acceptance Model in an ERP Implementation Environment. *Information and Management*, 41: 731-745.

Hadid, W., & Al-Sayed, M. 2021. Management Accountants and Strategic Management Accounting: The Role of Organizational Culture and Information Systems. *Management Accounting Research*, 50: 1-17.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R.E. 2010. *Multivariate Data Analysis: A Global Perspective*. Seventh Edition, New York: Pearson.

Hair, J. F., Ringle, C. M., & Sarstedt, M. 2011. PLS-SEM: Indeed a Silver Bullet. *The Journal of Marketing Theory and Practice*, 19(2): 139-152.

Hajri, Z. A., Xu, W., Nuwangi, S.M., & Sedera, D. 2014. Individual Innovative Use of ERP Systems. *Twenty Second European Conference on Information Systems*, Tel Aviv.

Hart, C. A., & Snaddon, D. A. 2014. The Organisational Performance Impact of ERP Systems on Selected Companies. *South African Journal of Industrial Engineering*, 25(1): 14-28.

Harpe, S. E. 2015. How to analyze Likert and other rating scale data. *Curr Pharm Teach Learn*, 7(6): 836-850.

Henseler, J., Ringle, C. M., & Sinkovics, R.R. 2015. The Use of Partial Least Squares Path Modeling in International Marketing. *In New Challenges to International Marketing*, 20: 277-319.

Heskett, J.L., Jones, T.O., Loveman, G.W., Sasser W.E., & Schlesinger L.A. 1994. Putting the Service-Profit chain to work. *Harvard Business Review*, March-April

Hoe, S. L. 2008. Issues and Procedures in Adopting Structural Equation Modeling Technique. *Journal of Applied Quantitative Methods*, 3(1): 77-83.

Hoque, Z., & James, W. 2000. Linking Balanced Scorecard Measures to Size and Market Factors: Impact on Organisational Performance. *Journal of Management Accounting Research*, 12: 1–17.

Hovorka, D., Germonprez, M., & Larsen, K. R. 2008. Explanation in Information Systems. *Information Systems Journal*, 18 :23-43.

Hočevar, B., & Jaklič. J. 2010. Assessing benefits of business intelligence systems- A case study. *Management*, 15 (1): 87-119.

Hou, C. K. 2018. Examining Users' Intention to Continue Using Business Intelligence Systems from the Perspectives of End-user Computing Satisfaction and Individual. *International Journal of Business Continuity and Risk Management,* 8(1): 49-70.

Hou, C. K. 2015. Using the Balanced Scorecard in Assessing the Impact of BI System Usage on Organisational Performance: An empirical study of Taiwan's Semi-conductor Industry. *Information Development*, 32:1545-1569.

Hou, C. H. 2012. Examining the Effects of User Satisfaction on System Usage and Individual Performance with Business Intelligence Systems: An empirical study of Taiwan's Electronics Industry. *International Journal of Information Management*, 32: 560-573.

Hsu, J. 2004. Data Mining and Business Intelligence: Tools, Technology, and Applications. In M. Raisinghani (Ed.), *Business intelligence in the digital economy*. London: Idea Group Publishing.

Huang, H.C. 2009. Designing a Knowledge-Based System for Strategic Planning: A Balanced Scorecard Perspective. *Expert Systems with Applications*, 36: 209–218.

Igbaria, M., & Tan, M. 1997. The Consequences of Information Technology Acceptance on Subsequent Individual Performance. *Information & Management*, 32(3): 113-121.

Iivari, J. 2005. An empirical test of DeLone-McLean model of Information Systems Success. *The DATA BASE for Advances in Information Systems*. 36(2): 8-27.

Isaac, O., Abdullah, Z., Ramayah, T., & Mutahar, A. M. 2017. Internet Usage, User Satisfaction, Task-technology Fit, and Performance Impact Among Public Sector Employees in Yemen. *The International Journal of Information and Learning Technology*, 34(3): 210-241.

Işik, Ö., Jones, M. C., & Sidorova, A. 2013. Business Intelligence Success: The Roles of BI Capabilities and Decision Environments. *Information & Management,* 50(1): 13-23.

Isik, Ö., Jones, M. C., & Sidorova, A. 2011. Business intelligence (BI) Success and the Role of BI Capabilities. *Intelligent Systems in Accounting, Finance and Management*, *18*(4): 161-176.

Jain, V., & Kanungo, S. 2005. Beyond Perceptions and Usage: Impact of Nature of Information Systems Use on Information System-Enabled Productivity. *International Journal of Human Computer Interaction*, 19(1): 113–136.

Jaklič, J., Grublješič, T., & Popovič, A. 2018. The Role of Compatibility in Predicting Business Intelligence and Analytics Use Intentions. *International Journal of Information Management*, 43: 305-318.

Jaklič, J., Coelho, P. S., & Popovič, A. 2009. Information Quality Improvement as a Measure of Business Intelligence System Benefits. *WSEAS Transactions on Business and Economics,* 9(6): 502-512.

Jasperson, J., Carter, P. E., & Zmud, R. W. 2005. A Comprehensive Conceptualization of Post-adoptive Behaviors Associated with Information Technology Enabled Work Systems. *MIS Quarterly*, *29*(3): 525-557.

Kaiser, H. F., & Rice, J .1974. Little Jiffy, Mark IV. *Educational and Psychological Measurement*, 34(1):111-117.

Kallunki, J.P., Laitinen, E.K., & Silvola, H. 2011. Impact of Enterprise Resource Planning Systems on Management Control Systems and Firm Performance. *International Journal of Accounting Information Systems*, 12: 20-39.

Kaplan, R.S. 1991. New Systems for Measurement and Control. *Engineering Economist,* 36(3): 201-218.

Kaplan, S., and McMillan D. 2021. Reimagining the Balanced Scorecard for the ESG Era. *Harvard Business Review.*

Kaplan, R.S., & Norton, D.P. 1992. The Balanced Scorecard – Measures that Drive Performance, *Harvard Business Review*, 70(1): 71-79.

Kaplan, R. S., & Norton, D. P. 1993. Putting the Balanced Scorecard to Work. *Harvard Business Review*, 71(5): 134–140.

Kaplan, R., & Norton, D. 1996. *The Balanced Scorecard: Translating Strategies into Action*. Boston, MA: Harvard Business School Press.

Kaplan, R., & Norton, D. 2001. *The Strategy-Focused Organisation: how Balanced Scorecard Companies Thrive in the New Business Environment.* Boston, MA: Harvard Business School Press.

Kaplan, R. S., & Norton, D. P. 2006. *Alignment: Using the Balanced Scorecard to Create Corporate Synergies*, Boston, MA: Harvard Business School Press

Ketokivi, M. 2006. Elaborating the Contingency Theory of Organisations: The Case of Manufacturing Flexibility Strategies Production and Operations Management. *Production and Operations Management Society*, 15(2): 215–228.

Kihn, L. 2010. Performance Outcomes in Empirical Management Accounting Research. *International Journal of Productivity and Performance Management*, 59(5): 468-492.

Kim, S. S. 2009. The Integrative Framework of Technology use: An Extension and Test. *MIS Quarterly*, *33*(3): 513-537.

Kim, S. S., & Malhotra, N. K. 2005. A longitudinal model of continued is use: An integrative view of four mechanisms underlying postadoption phenomena. *Management Science*, *51*(5): 741-755.

Kjeldskov, J., Skov, M. B., & Stage, J .2010. A longitudinal Study of Usability in Health Care: Does Time Heal? *International Journal of Medical Informatics,* 79: 135-143.

Kreutzer, M., Cardinal, L. B., Walter, J., & Lechner, C. 2016. Formal and Informal Control as Complement or Substitute? The Role of the Task Environment. *Strategy Science*, *1*(4), 235-255.

Kopáčková, H., & M. Škrobáčková. 2006. Decision Support Systems or Business Intelligence: what can help in decision making? *Scientific papers of the University of Pardubice*. Series D, Faculty of Economics and Administration, 10.

Kubina, M., Koman, G., & Kubina, L. 2015. Possibility of Improving Efficiency within Business Intelligence Systems in Companies. *Procedia Economics and Finance*, 26: 300-305.

Laguir, L., Laguir, I., & Tchemeni, E. 2019. Implementing CSR activities through management control systems: A Formal and Informal Control Perspective. *Accounting, Auditing & Accountability Journal*, 32(2): 531-555.

Laumer, S., Maier, C., Eckhardt, A., & Weitzel, T. 2016. Work Routines as an Object of Resistance During Information Systems Implementations. Theoretical foundation and empirical evidence. *European Journal of Information Systems*, 25(4): 317-343.

Laumer, S., Christian, M., & Waitzel, T. 2017. Information Quality, User Satisfaction, and the Manifestation of Workarounds: A Qualitative and Quantitative Study of Enterprise Content Management System Users. *European Journal of Information Systems*, 26(4): 333-360.

Lautenbach, P., Johnston, K., & Adeniran-Ogundipe, T. 2017. Factors Influencing Business Intelligence and Analytics Usage Extent in South African Organisations. *South African Journal of Business Management*, 48 (3): 23-33.

Lee, M.T., & Widener, S.K. 2013. Culture and Management Control Systems in Today's High-Performing Firms. *Management Accounting Quarterly Winter*, 14(2): 11-18.

Lee, S., Park, S. B., & Lim, G. G. 2013. Using Balanced Scorecards for the Evaluation of Software-as-a-service. *Information and Management*, 50: 553-561.

Lee, N., & Lings, I. 2008. *Doing business research: A Guide to Theory and Practice*. London: SAGE.

Lee, B., Barua, A., & Whinston, A.B. 1997. Discovery and Representation of Causal Relationships in MIS Research: A Methodological Framework. *MIS Quarterly*, 21(1): 109-136.

Legodi, I., & Barry, M. 2010. The current challenges and Status of Risk Management in Enterprise Datawarehouse Projects in South Africa. *In Technology Management for Global Economic Growth:*1-5.

Li, X., Hsieh, J. J. P., & Rai, A. 2013. Motivational Differences Across Post-Acceptance Information System Usage Behaviors: An Investigation in the Business Intelligence Systems Context. *Information Systems Research*, 24: 659-682.

Li, Y., Yuan, X., & Che, R. 2021. An Investigation of Task Characteristics and Users' Evaluation of Interaction Design in Different Online Health Information Systems. *Information Processing and Management*, 58: 1-20.

Li, Y., & Liu, C. 2019. Information Resource, Interface, and Tasks as User Interaction Components for Digital Library Evaluation. *Information Processing & Management*, 56: 704-720.

Liew, A. 2019. Enhancing and Enabling Management Control Systems through Information Technology: The Essential Roles of Internal Transparency and Global Transparency. *International Journal of Accounting Information Systems,* 33: 16-31.

Lin, Y. H., Tsai, K.M., Shiang, W. J., Kuo, T.C., & Tsai, C.H. 2009. Research on Using ANP to Establish a Performance Assessment Model for Business Intelligence Systems. *Expert Systems with Applications*, 36: 4135-4146.

Liu, P., & Li, Z. 2012. Task complexity: A review and Conceptualization Framework. *International Journal of Industrial Ergonomics*, 42(6): 553-568.

Lönnqvist, A., & Pirttimäki, V. 2006. The Measurement of Business Intelligence. *Information Systems Management*, 23(1): 32-40.

Lucadamo, A., & Amenta, P. 2014. A New Scaling Proposal for Handling Ordinal Categorical Variables in Co-Inertia (-PLS) Analysis. *Procedia Economics and Finance*, 17: 10-19.

Luo, Y., Ling, H., Zhang, C., & Xu, Y. 2012. Individual and Collective Innovative Use of Enterprise System-Mediating Role of Collective Learning. *Pacific Asia Conference on Information Systems* (PACIS 2012).

Markus, M. L., & Robey, D. 1988. Information Technology and Organisational Change: Causal Structure in Theory and Research, *Management Science,* 34(5): 583-598.

Markus, L. M., & Rowe, F. 2018. Is IT Changing the World? Conceptions of Causality for Information Systems Theorizing. *MIS Quarterly*, 42(4), 1255-1280.

Martin, M.A. 2020. An Evolutionary Approach to Management Control Systems Research: A Prescription for Future Research. *Accounting, Organisations and Society*, 86: 101186.

Maldifassi, J. O., & Crovetto, P. 2013. Enablers and Difficulties for Innovation in Chile: Perceptions from Medium Size Plastic Firm Managers. *Journal of Technology Management & Innovation,* 8(1): 35-43.

Malmi, T., & Brown, D.A. 2008. Management Control Systems as a Package—Opportunities, Challenges and Research Directions. *Management Accounting Research*, 19: 287-300.

Malmi, T., Bedford, D. S., Brühl, R., Dergård, J., Hoozee, S., Janschek, O., Willert, J., Ax, C., Bednarek, P., Gosselin, M., Hanzlick, M., Israelsen, P., Johanson, D., Johanson, T., Madsen, D. Ø., Rohde, C., Sandelin, M., Strömsten, T., & Toldbod, T. 2020. Culture and Management Control Interdependence: An Analysis of Control Choices That Complement the Delegation of Authority in Western Cultural Regions. *Accounting, Organisations and Society,* 86*:*101116 Retrieved from: https://doi.org/10.1016/j.aos.2020.101116.

Maxwell, J. A. 2005. *Qualitative Research Design: An Interactive Approach*. SAGE. [online], Retrieved from:http://www.corwin.com/upm-data/23772_Ch7.pdf.

Merchant, K. A., & van der Stede W.A. 2007. Management Control Systems. Pearson Education Limited, Edinburgh Gate, England.

Mendoza, A., Carroll, J., & Stern, L. 2008. Influences on Continued Use of an Information System: A Longitudinal Study. *ECIS 2008 Proceedings*, 161

Mertens, D. M. 2004. *Research and Evaluation in Education and Psychology: Integrating Diversity with Quantitative, Qualitative and Mixed Methods*. 2nd Edition. San Francisco, CA.: SAGE Publications.

Mingers, J. 2004. Re-Establishing the Real: Critical Realism and Information Systems, in Social Theory and Philosophy for Information Systems. *MIS Quarterly*, 1:1-29

Mingers, J., Mutch, A., and Willcocks, L. 2013. Critical Realism in Information Systems Research. *MIS Quarterly,* 37(3): 795-802.

Mircea, M., & Andreescu, A. 2009. Using Business Rules in Business Intelligence. *Journal of Applied Quantitative Methods,* 4(1): 382-393.

Mohamad, W., Bin, A., & Afthanorhan, W. 2014. Hierarchical Component Using Reflective-Formative Measurement Model in Partial Least Square Structural Equation Modeling (pls-Sem). *International Journal of Mathematics and Statistics Invention*, 2(2): 55-71.

Morton, N. A., & Hu, Q. 2008. Implications of the Fit Between Organisational Structure and ERP: A Structural Contingency Theory Perspective. *International Journal of Information Management,* 28: 391-402.

Montero, J. N. 2019. *Determining Business Intelligence System Usage Success Using the DeLone and McLean Information System Success Model* (Doctoral dissertation, Capella University).

Mou, J., & Cohen, J. 2008. Illustrating the Use of Cross-Lagged Structural Equation Modelling to Examine Causal Ordering: An Example Using Trust and Risk in Online Health Services. *Thirty Ninth International Conference on Information Systems,* San Francisco 2018.

Mudzana, T., & Maharaj, M. 2017. Toward an Understanding of Business Intelligence Systems Success: A South African Study. *The Electronic Journal Information Systems Evaluation*, 20(1): 24-38.

Muhammad, G., Ibrahim, J., Bhatti, Z., & Waqas, A. 2014. Business Intelligence as a Knowledge Management Tool in Providing Financial Consultancy Services. *American Journal of Information Systems,* 2 (2): 26-32

Murray, J. 2013. Likert Data: What to Use, Parametric or Non-Parametric?. *International Journal of Business and Social Science,* 4(11): 258-264.

Muzaffar, B. 2016. The Development and Validation of a Scale to Measure Training Culture: The TC Scale. *Journal of Culture, Society and Development*, 23: 49-58.

Myung, I.N. 2003. Tutorial on Maximum Likelihood Estimation. *Journal of Mathematical Psychology*, 47: 90-100.

Nadia, A. 2014. Interaction Between Management Control and Business Intelligence in Public Economic Companies of Tlemcen. *International Journal of Enhanced Research in Management & Computer Applications*, 3(3): 71-78.

Nappo, D., & Grassia, M.G. 2008. An Altering Least Square Approach for the Estimation of a SEM Based on Ordinal Variables. *Statistica Applicata*, 20 (3): 293-307.

Narayanan, V. and Boyce, G. 2019. Exploring the Transformative Potential of Management Control Systems in Organisational Change Towards Sustainability. *Accounting, Auditing & Accountability Journal*, 32(5): 1210-1239.

Neely, A., Gregory, M., & Platts, K. 2005. Performance Measurement System Design. *International Journal of Operations and Production Management*, 25(12): 1228-1263.

Negash, S. 2004. Business Intelligence. *Communications of the Association for Information Systems*, 15(13):177-195.

Nespeca, A., & Chiucchi, M.S. 2018. *The Impact of Business Intelligence Systems on Management Accounting Systems: The Consultant's Perspective*. Springer Cham. [Online], Retrieved from: https://doi.org/10.1007/978-3-319-62636-9_19.

Nielsen, S. 2018. Reflections on the Applicability of Business Analytics for Management Accounting and Future Perspectives for the Accountant. *Journal of Accounting & Organizational Change*,14(2): 167-187.

Nkwe, N. 2018. Developing and Validating Measurement Items for a Multi-dimensional Social Network Site Usage Construct. *The African Journal of Information Systems*, 10(4): 313-338.

Nofal, M.I., & Yusof, Z. M. 2013. Integration of Business Intelligence and Enterprise Resource Planning within Organisations. *Procedia Technology*, 11: 658-665

Norman, G. 2010. Likert Scales, Levels of Measurement and the Laws. *Adv in Health Sci Educ*, 15: 625-632.

Noor, U. L., Giovanni, V., & DeLone, W. 2019. Business Intelligence System Adoption, Utilization and Success-A systematic literature review. *Proceedings of the 52nd Hawaii International Conference on System Sciences.*

O'Brien, J., & Kok, J. 2006. Business Intelligence and the Telecommunications Industry: can Business Intelligence Lead to Higher Profits?, *South African Journal of Information Management*, 8(3): 1-16.

Ojo, A. I. 2017. Validation of the DeLone and McLean Information Systems Success Model. *Healthcare Informatics Research*, 23(1): 60-66.

Olszak, C. M., & Ziemba, E. 2003. Business Intelligence as a Key to Management of an Enterprise. *Proceedings of Informing Science and IT Education Conference*,[online], Available at:http://proceedings.informingscience.org/IS2003Proceedings/docs/109Olsza.pdf [Accessed 4th February 2016].

Olszak, C. M., & Ziemba, E. 2006. Business Intelligence Systems in the Holistic Infrastructure Development Supporting Decision-making in Organisations. *Interdisciplinary Journal of Information, Knowledge and Management*, 1, 47-58.

Olszak, C., & Ziemba, E. 2012. Critical Success Factors for Implementing Business Intelligence Systems in Small and Medium Enterprises. *Interdisciplinary Journal of Information, Knowledge, and Management*, 7: 130-150.

Otley, D. 1980. The Contingency Theory of Management Accounting: Achievement and Prognosis. *Accounting, Organisations and Society*, 5(4): 413-428.

Otley, D. 2003. Management Control and Performance Management: Whence and Whither?. *The British Accounting Review*, 35: 309-326.

Owusu, A. 2017. Business Intelligence Systems and Bank Performance in Ghana: The Balanced Scorecard Approach. *Cogent Business & Management*, 4 (1): 1-22.

Paré, G., Trudel, M. C., Jaana, M., & Kitsiou, S. 2015. Synthesizing Information Systems Knowledge: A Typology of Literature Reviews. *Information and Management*, 52(2), 183-199.

Paré, G., Guillemette, M.G., & Raymond, L. 2020. IT centrality, IT Management Model, and Contribution of the IT Function to Organisational Performance: A Study in Canadian Hospitals. *Information and Management*, 57: 103198.

Papageorgiou, E., & Bruyn, H.D. 2010. Using Executive Information Systems as a Business Management Tool in Listed Johannesburg Stock Exchange (JSE) Companies: An Exploratory Study. *Acta Commecii*, 203-217

Papageorgiou, E., & De Bruyn, H.D. 2011. Challenges of Executive Information Systems in listed Johannesburg Stock Exchange companies. *SA Journal of Information Management*, 13(1):448-458.

Peters, M., Wieder, B., and Sutton, S. 2018. Organizational Improvisation and the Reduced Usefulness of Performance Measurement BI Functionalities. *International Journal of Accounting Information Systems,* 29: 1-15.

Peters, M. D., Wieder, B., Sutton, S.G., & Wakefield, J. 2016. Business Intelligence Systems use in Performance Measurement Capabilities: Implications for Enhanced Competitive Advantage. *International Journal of Accounting Information Systems*, 21: 1-17.

Petrini, M., & Pozzebon, M. 2009. Managing Sustainability with the Support of Business Intelligence: Integrating Socio-environmental Indicators and Organisational Context. *Journal of Strategic Information Systems,* 18:178-191.

Petter, S., DeLone, W.H., & McLean, E.R. 2008. Measuring Information Systems Success: Models, Dimensions, Measures, and Interrelationships. *European Journal of Information Systems,* 17: 236-263.

Petter, S., DeLone, W., & McLean, E.R. 2013. Information Systems Success: The Quest for the Independent Variables. *Journal of Management Information Systems*. 29, 7-62.

Petty, N.J., Thomson, O.P., & Graham, S. 2012. Ready for a Paradigm Shift? Part 2: Introducing Qualitative Research Methodologies and Methods. *Manual therapy,* 17: 378-384.

Pirttimäki, V., Lönnqvist, A., & Karjaluoto, A. 2006. Measurement of Business Intelligence in a Finnish Telecommunications Company. *Electronic Journal of Knowledge Management,* 4(1): 83-90.

Ponniah, P. 2010. *Data Warehousing Fundamentals for IT Professionals*. Hobokken, New Jersey: John Wiley & Sons.

Ponterotto, J.G. 2005. Qualitative Research in Counselling Psychology: A Primer on Research Paradigms and Philosophy of Science. *American Psychological Association*, 52(2): 126-136.

Poorundersing, T.S.B. 2008. The Effectiveness of Management Accounting Systems. *Managerial Auditing Journal*, 23 (2):187-219.

Popovič, A., Hackney, R., Coelho, P.S., & Jaklič, J. 2012. Towards Business Intelligence Systems Success: Effects of Maturity and Culture on Analytical Decision Making. *Decision Support System*, 54: 729- 739.

Popovič, A., Hackney, R., Coelho, P.S., & Jaklič, J. 2014. How Information-Sharing Values Influence the Use of Information Systems: An Investigation in the Business Intelligence Systems Context. *Journal of Strategic Information Management*, 1: 1- 14.

Popovič, A., Tomaž, T., & Jaklič, J. 2010. Conceptual Model of Business Value of Business Intelligence Systems. *Management*, 15 (1): 5-30.

Popovič, A., Hackney, R., Tassabehji, R., & Castelli, M. 2018. The Impact of Big Data Analytics on Firms' High Value Business Performance. *Information System Frontiers*, 20: 209-222.

Popovič, A. 2017. If we Implement it, will they come? User Resistance in Post-Acceptance Usage Behaviour within a Business Intelligence Systems Context, *Economic Research-Ekonomska Istraživanja*, 30(1): 911-921.

Power, D. 2007. *A Brief History of Decision Support Systems*. [Online], Available at: <http://dssresources.com/history/dsshistory.html/, [Accessed 1st January 2017].

PFMA. 1999. *Public Finance Management Act No 1*. National Treasury: Pretoria.

Puklavec, B., Oliveira., T. & Popovič, A. 2018. Understanding the Determinants of Business Intelligence System Adoption Stages: An Empirical Study of SMEs. *Industrial Management and Data Systems*, 118 (1): 236-261.

Puklavec, B., Oliveira, T., & Popovic, A. 2014. Unpacking Business Intelligence Systems Adoption Determinants: An exploratory study of small and medium enterprises. *Economic and Business Review*, 16:185-213.

Quesado, P., Guzmán, B. A., & Rodrigues, L. L. 2017. Advantages and Contributions in the Balanced Scorecard Implementation. *Intangible Capital,* 14(1): 186-201.

Quattrone, P., & Hopper, T. 2005. A time–Space Odyssey: Management Control Systems in Two Multinational Organisations. *Accounting, Organisations and Society*, 30: 735-764.

Ramanathan, R., Philpott, E., Duan, Y., & Cao, G. 2017. Adoption of Business Analytics and Impact on Performance: A Qualitative Study in Retail. *Production Planning and Control,* 28(11-12): 985-998.

Ranjan, J. 2009. Business Intelligence: Concepts, Components, Techniques and Benefits. *Journal of Theoretical and Applied Information Technology*, 9(1): 60-70.

Rauhamäki, J. 2014. *Business Intelligence and Management Controls* (Master's thesis, University of Turku). [online], Available at:https://www.utupub.fi/bitstream/handle/10024/97244/414411.pdf?sequence=2, [Accessed: 7 January 2021].

Rikhardsson, P., & Yigitbasioglu, O. 2018. Business Intelligence & Analytics in Management Accounting Research: Status and Future Focus. *International Journal of Accounting Information Systems*, 29: 37-58.

Ritacco, M. & Carver, A. 2007. The Business Value of Business Intelligence: A Framework for Measuring the Benefits of Business Intelligence. *Business Objects*, 1-24.

Rogers, E. M. 1965. *Diffussion of innovations*, Glencoe: Free Press.

Rom, A. & Rohde, C. 2006. Enterprise Resource Planning Systems, Strategic Enterprise Management Systems and Management Accounting: A Danish study. *Journal of Enterprise Information Management*, 19(1): 50-66.

Russolillo, G. 2012. Non-Metric Partial Least Squares. *Electronic Journal of Statistics,* 6: 1641-1669.

Saavedra, M. S. M., & Batch, C. 2017. Factors to Determine Business Intelligence Implementation in Organizations. *European Journal of Engineering Research and Science*, 2(12): 1-7.

Sageder, M., & Feldbauer-Durstmüller, B. 2019. Management Control in Multinational Companies: A Systematic Literature Review. *Rev Manag Sci*, 13**:** 875-918.

Salkind, N. 2009. *Exploring research*. 7th ed. Upper Saddle River, New Jersey: Pearson Prentice Hall.

Sangthong, M. 2020. The Effect of the Likert Point Scale and Sample Size on the Efficiency of Parametric and Nonparametric Tests. *Thailand Statistician*, 18(1): 55-64.

Sanchez-Rodriguez, C., & Spraakman, G. 2012. ERP Systems and Management Accounting: A Multiple Case Study, *Qualitative Research in Accounting & Management,* 9 (4).

SAP. 2015. *Annual Report*. [Online], Available at:http://go.sap.com/docs/download/investors/2015/sap-2015-annual-report.pdf/, [Accessed 21 August 2016].

Saunders, M., Thornhill, A., & Lewis, P. 2009. *Research Methods for Business Students*. 5th Edition. Upper Saddle River, NJ: Pearson Education.

Sandelin, M. 2008. Operation of Management Control Practices as a Package-A Case Study on Control System Variety in a Growth Firm Context. *Management Accounting Research*. 19(4): 324-343.

Schierder, C., & Gluchowski, P. 2011. Towards a Consolidated Research Model for Understanding Business Intelligence Success. *ECIS Proceedings*, 205:1-11.

Schmiedel, T., Vom Brocke, J., & Recker, J. 2014. Development and Validation of an Instrument to Measure Organisational Cultures' Support of Business Process Management. *Information & Management*, 51(1):43-56.

Seashore, S. E., & Yuchtman, E. 1967. Factorial Analysis of Organisational Performance. *Administrative Science Quarterly*, 377-395.

Serumaga-Zake, P.A.E. 2017. The Role of User Satisfaction in Implementing a Business Intelligence System. *South African Journal of Information Management,* 19(1): 1-8.

Serrano Archimi, C., Reynaud, E., Yasin, H. M., & Bhatti, Z. A. 2018. How Perceived Corporate Social Responsibility Affects Employee Cynicism: The Mediating Role of Organisational Trust. *Journal of Business Ethics*, 151(4): 907-921.

Sedera, D., & Gable, G. 2004. Factor and Structural Equation Analysis of the Enterprise Systems Success Measurement Model. *ICIS Proceedings,* 6:449-464.

Skyrius, R., Kazakevičienė, G., & Bujauskas, V. 2013. From Management Information Systems to Business Intelligence: The Development of Management Information Needs. *International Journal of Artificial Intelligence and Interactive Multimedia*, 2(3): 31-37.

Shang, S., & Seddon, B.P. 2002. Assessing and Managing the Benefits of Enterprise Systems: The Business Manager's Perspective. *Information Systems Journal,* 12(4):271-299.

Simons, R. 1987. Accounting Control Systems and Business Strategy: An Empirical Analysis, *Accounting, Organisations and Society,* 12(4): 357-374.

Smith, M. L. 2006. Overcoming Theory-Practice Inconsistencies: Critical Realism and Information Systems Research. *Information and Organisation*, 16(3): 191-211.

Smith, K. L. 2007. A Review of Quantitative Research in Management Control Systems and Strategy. *Handbook of Management Accounting Research,* 3: 753-783.

Son, X., & Taamouti, A. 2019. A Better Understanding of Granger Causality Analysis: A Big Data Environment. *Oxford Bulletin of Economics and Statistics,* 81(4): 911-936.

Sutton, S. G. 2006. Enterprise Systems and the Re-shaping of Accounting Systems: A Call for Research. *International Journal of Accounting Information Systems*,7: 1-6.

Sun, J., & Teng, J.T.C. 2017. The Construct of Information Systems Use Benefits: Theoretical Explication of its Underlying Dimensions and the Development of a Measurement Scale. *International Journal of Information Management,* 37(5): 400-416.

Sun, Z., Strang, K., & Firmin, S. 2017. Business Analytics-Based Enterprise Information Systems. *The Journal of Computer Information Systems*, 57(2):169-178.

Sun, Z; Sun, L; Strang, K. 2018. Big Data Analytics Services for Enhancing Business Intelligence. *Journal of Computer Information Systems*, 58(2):162-169.

Tam, C., & Oliveira, T. 2017. Understanding Mobile Banking Individual Performance: The DeLone & McLean Model and the Moderating Effects of Individual Culture. *Internet Research*, 27(3): 538-562.

Tan, H. 2017. A Brief History and Technical Review of The Expert System Research. *Materials Science and Engineering*, 242: 1-5.

Tarka, P. 2018. An Overview of Structural Equation Modeling: its Beginnings, Historical Development, Usefulness and Controversies in The Social Sciences. *Quality & quantity*, 52(1): 313-354.

Teece, D. J. 2014. A Dynamic Capabilities-Based Entrepreneurial Theory of the Multinational Enterprise. *Journal of International Business Studies*, 45(1): 8-37.

Thompson, O. 2004. Business intelligence success, lessons learned. *Technology*. [Online], Available at :http://www.ism.co.at/analyses/Business_Intelligence/Success_Analysis.html/ ,[Accessed 30 June 2020].

Tomic, D. 2006. Business Intelligence in Management Accounting. *SEE Journal*, 1(1): 80-89.

Torkzadeh, G., & Doll., W.J. 1999. The development of a tool for measuring the perceived impact of information technology on work. *Omega*, 27(3): 327-339.

Torres, R., & Sidorova, A. 2019. Reconceptualizing Information Quality as Effective Use in the Context of Business Intelligence and Analytics. *International Journal of Information Management*, 49: 316-329.

Torres, R., Sidorova, A., & Jones, M. C. 2018. Enabling Firm Performance Through Business Intelligence and Analytics: A Dynamic Capabilities Perspective. *Information & Management*, *55*(7): 822-839.

Tsui, J. S. L. 2001. The Impact of Culture on the Relationship Between Budgetary Participation, Management Accounting Systems, and Managerial Performance: An analysis of Chinese and Western managers. *The International Journal of Accounting*, 36: 125-146.

Tucker, B., & Parker, L. 2014. In Our Ivory Towers? The Research-Practice Gap in Management Accounting. *Accounting and Business Research*, 44 (2):104-143.

Uppatumwichian, W. 2013. An Empirical Investigation on Business Intelligence Use In Budgeting. *ECIS 2013 Completed Research:* 106.

Vakalfotis, N., Ballantine, J., & Wall, A. 2011. A literature Review on the Impact of Enterprise Systems on Management Accounting. *International Conference on Enterprise Systems Accounting and Logistics*, July 11-12, Thassos Island, Greece.

Vallurupalli, V., & Bose, I. 2018. Business Intelligence for Performance Measurement: A Case Based Analysis. *Decision Support Systems*, 111: 72-85.

Venkatesh, V., & Davis, F.D. A. 2000. Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science,* 46 (2):186-204.

Venter, P., & Tustin, D. 2009. The Availability and Use of Competitive and Business Intelligence in South African Business Organisations. *Southern African Business Review*, 13(2): 88-117.

Velcu, O. 2007. Exploring the Effects of ERP Systems on Organisational Performance. *Industrial Management & Data Systems*, 107(9): 1316-1334.

Vidgen, R., Shaw, S., & Grant, D. B. 2017. Management Challenges in Creating Value from Business Analytics. *European Journal of Operational Research*, 261(2): 626-639.

Vonglao, P. 2017. Application of fuzzy logic to improve the Likert scale to measure latent variable. *Kasetsart J Soc Sci*, 38(3): 337-344.

Wang, Y. S., Wang, H. Y., & Shee, D. Y. 2007. Measuring E-learning Systems Success in an Organisational Context: Scale Development and Validation. *Computers in Human Behavior*, 23(4):1792-1808.

Waterhouse, J., & Tiessen, P. 1978. A Contingency Framework for Management Accounting Systems Research. *Accounting, Organisations and Society*, 3(1):65–76.

Watson, H. J., & Wixom, B.J. 2007. The Current State of Business Intelligence. *Computer Society*, 40(9): 96-99.

Webster, J., & Watson, R. T. 2002. Analyzing The Past to Prepare for The Future: Writing a Literature Review. *MIS quarterly*, 26(2): 13-23.

Wier, B., Hunton, J., & Hassab Elnaby, H. R. 2007. Enterprise Resource Planning Systems and Non-financial Performance Incentives: The Joint Impact on Corporate Performance. *International Journal of Accounting Information Systems*, 8(3):165–90.

Wierder, B., & Ossimitz, M. 2015. The Impact of Business Intelligence on the Quality of Decision Making – a Mediation model. *Procedia Computer Science* 64: 1163-1171.

William, S., & Williams, N. 2007. *The Profit Impact of Business Intelligence*. London, U.K, Elsevier Inc.

Wixom, B., & Watson, H. J. 2010. The BI-based Organisation. *International Journal of Business Intelligence Research*, 1: 13-28.

Wu, I. L., & Chen, J. L. 2014. A Stage-based Diffusion of IT Innovation and the BSC Performance Impact: A moderator of Technology- organisation-environment. *Technological Forecasting and Social Change*, 88: 76-90.

Wu, J. H., & Wang, Y. M. 2006. Measuring KMS Success: a Respecification of the DeLone and McLean's Model. *Information & Management*, 43(6): 728-739.

Yakubu, M. N., & Dasuki, S. I. 2018. Assessing eLearning systems success in Nigeria: An application of the DeLone and McLean information systems success model. *Journal of Information Technology Education: Re-search*, 17: 182-202.

Yurek, L. A., Vasey, J., & Havens, D. S. 2008. The Use of Subject-Generated Identification Codes in Longitudinal Research. *Evaluation Review*, 32(5): 435-452.

Zheng, Z., & Pavlou, P.A. 2010. Toward a Causal Interpretation from Observational Data: A New Bayesian Networks Method for Structural Models with Latent Variables. *Information Systems Research*, 21(2): 365-391.

Zmud, R. W., & Apple, L. E. 1992. Measuring Technology Incorporation /Infusion. *Journal of Production Innovation Management*, 9: 145-155.

APPENDIX A: PARTICIPATION INVITATION LETTER AND INDIVIDUAL USE INSTRUMENTS W1

Part A: Demographic Information

Participation Invitation Letter (Individual use) (Wave 1)

Good day,

My name is Thanyani Norman Mudau, and I am a Doctoral student in accountancy at the University of the Witwatersrand (WITS), Johannesburg. As a degree requirement at WITS, I am conducting a study on the use and impact of Business Intelligence (BI) Systems. The purpose of the study is to investigate the factors influencing the innovative use of BI systems by individuals in the management accounting context in South Africa and the impacts of such use of BI systems on management accountant's individual performance. BI systems are defined as information systems software that is used for the purpose of gathering, managing, analysing, and sharing information about external and internal environment to gain insights for better decision making.

As a user of your organisation's BI system, you are invited to take part in this study by completing this questionnaire. The questionnaire deals with your perceptions about your use of the BI system and its impact on your performance. Your response is important and there are no right or wrong answers. This survey is both **confidential and anonymous**. **Anonymity and confidentiality** are guaranteed by not needing to enter your name on the questionnaire. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the survey at any stage. The study will be conducted over three stages (waves) 12 weeks apart. This is to allow the researcher to measure BI system use over a period. However, participants do not have to participate in all three stages and participation in each stage is voluntary. This is the first survey and invites all BI system users irrespective of the number of years using the BI tool.

The first part of the survey captures some demographic data, by selecting the appropriate response. The second part of the survey comprises 64 statements. Please indicate the extent to which you agree with each statement, by ticking in the appropriate box. The entire survey should take between 10 to 20 minutes to complete. The survey was approved by the Wits Human Research Ethics Committee (HREC Non-Medical), Protocol Number: H17/04/22.

Should you have any questions, or wish to obtain a copy of the results of the survey in aggregate form, please contact me on +27 82 611 7131 or at mudauno@yahoo.com.
My supervisor's names and email addresses: Prof Jason Cohen- Jason.cohen@wits.ac.za
:Prof Elmarie PapaGeorgiou-Elmarie.Papageorgiou@wits.ac.za

Thank you for considering your participation

Kind regards,
Thanyani Norman Mudau
Faculty of commence, law and management
School of Accountancy
University of the Witwatersrand (WITS), Johannesburg

The Survey is divided into <u>two sections</u>
Part A: Demographic information
Part B: BI system use

This section asks questions about your demographic information including your experience.

The survey is divided into two section

1. Please select your age

18-24	
25-29	
30-35	
36-40	
41-45	
46-50	
51-55	
56 >	
Prefer not to say	

2. Please select your gender

Female	
Male	
Prefer not to say	

3. Please select your years of experience in management accounting within your current organisation.

<2 years	
2-5 years	
6-9 years	
10-15 years	
16-19 years	
>20 years	

4. Please select your years of experience in management accounting within your current organisation.

<2 years	
2-5 years	
6-10 years	

11-15 years	
16-20 years	
>21 years	

5. Please select your total years of experience using BI systems

<2 years	
2-5 years	
6-10 years	
11-15 years	
16-20 years	
>21 years	

6. Please select the BI system you currently use in your role as a management accountant within your organisation.

None	
SAP business object	
Oracle Hyperion	
SAS	
Oracle	
Microsoft	
MicroStrategy	
IBM Cognos	
Qlikeview	
SAGE	
Sisense	
Sybase IQ	
ASYST	
Synergy	
Clear Analytics (Excel based)	
Other (please specify)	

7. Please select your total years of experience using BI systems with your current organisation.

None	
<1 years	
1-2 years	
3-5 years	
6-9 years	
>10 years	

8. Please select if you have attended any formal training programme on BI system use.

Yes	
No	
Prefer not to say	

9. Please select the industry sector, in which you are working as a management accountant.

Manufacturing	
Utilities and energy	
Logistics	
Retail	
Telecom	
Airline	
Pharmaceutical	
Public sector	
Service	
Finance	
Mining	
Accounting	
Other (please specify)	

10. Which of the following best describes your management level?

Junior	
Entry management	
Middle Management	
Senior Manager	
Specialist	
Executive management	
Other (please specify)	

11. Please select your professional membership(s).

CIMA	
SAICA	

Other (please specify)	

12. Please indicate the following in order to facilitate the matching of responses across subsequent waves of the survey while retaining your anonymity.

Items	
State your month of birth (i.e. January)	
State first three letters of your mother's first name	

Part B: Perceptions and Use of BI System

The purpose of this section is to obtain your perceptions about your BI system use.

13. Please indicate the extent in which you agree with each of the following statements related to the BI system that you currently use in your work as a management accountant. Please indicate whether you Strongly disagree, Mostly disagree, Disagree, are Neutral, Agree, Mostly agree or Strongly Agree with each statement.

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
SQ1	The BI system is always up and running	1	2	3	4	5	6	7
SQ2	The BI system is easy to navigate	1	2	3	4	5	6	7
SQ3	The response time of BI system is acceptable	1	2	3	4	5	6	7
SQ4	The BI system is easy to use	1	2	3	4	5	6	7
SQ5	The BI system is user friendly	1	2	3	4	5	6	7
SQ6	The BI system is stable	1	2	3	4	5	6	7
DQ1	Data inputs records in the system are always complete	1	2	3	4	5	6	7
DQ2	Data records in the system are never missing	1	2	3	4	5	6	7
DQ3	Data records in the system are always correct	1	2	3	4	5	6	7
IQ1	Information output by the BI system is presented in a useful format	1	2	3	4	5	6	7
IQ2	Information output by the BI system is accurate	1	2	3	4	5	6	7
IQ3	Information output provided by the BI system is easy to understand	1	2	3	4	5	6	7
IQ4	Information output provided by the BI system meets my needs	1	2	3	4	5	6	7
IQ5	Information output provided by the BI system is relevant	1	2	3	4	5	6	7
IQ6	Information output produced by BI system is complete with no need to rely on other systems	1	2	3	4	5	6	7
IQ7	Information output provided by BI systems is important and helpful for my work	1	2	3	4	5	6	7
SQa1	My organisation’s BI system support team is always helpful to me	1	2	3	4	5	6	7
SQa2	My organisation’s BI system support team is responsive within reasonable time	1	2	3	4	5	6	7
SQa3	My organisation’s BI system support team is committed in resolving my systems challenges	1	2	3	4	5	6	7
SQa4	My organisation’s BI system support team respond to my request promptly	1	2	3	4	5	6	7
SQa5	With the support that I have received I believe I can now use the BI system with confidence	1	2	3	4	5	6	7
US1	I enjoy using the BI system	1	2	3	4	5	6	7
US2	I would recommend the BI system to other management accountants	1	2	3	4	5	6	7
US3	The BI system works the way I want it to work	1	2	3	4	5	6	7

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
US4	It is pleasant to use the BI system	1	2	3	4	5	6	7
US5	Overall, I am satisfied with BI system	1	2	3	4	5	6	7
IP 1	Using the BI system improves my job performance	1	2	3	4	5	6	7
IP 2	Using the BI system increases my work productivity	1	2	3	4	5	6	7
IP 3	Using the BI system enhances my effectiveness in my job	1	2	3	4	5	6	7
IP 4	Using the BI system improves my decision-making quality	1	2	3	4	5	6	7
IP 5	Using the BI system helps me to identify potential problems faster.	1	2	3	4	5	6	7
IP 6	Using BI system assist me in making decisions quicker	1	2	3	4	5	6	7
IP 7	Using BI system assist me to spend less time in meetings	1	2	3	4	5	6	7
SI1	I could use more advanced features of a BI tool with only the built-in help functions for assistance.	1	2	3	4	5	6	7
SI2	I am confident in my ability to use the more advanced features of a BI tool	1	2	3	4	5	6	7
SI3	I am confident in my ability to use a BI system to predict the future performance of the organisation.	1	2	3	4	5	6	7

14. Please indicate the extent in which you agree with each of the following statements related to the complexity of your work as a management accountant.

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
TC1	The work that I perform is routine.	1	2	3	4	5	6	7
TC2	My co-workers perform the same job in the same way most of the time.	1	2	3	4	5	6	7
TC3	The duties that I perform are repetitious.	1	2	3	4	5	6	7
TC4	My co-workers perform repetitive activities in doing their jobs.	1	2	3	4	5	6	7
TC5	There is a clearly known way to do the major types of work I normally encountered.	1	2	3	4	5	6	7
TC6	There is a clearly defined body of knowledge of subject matter which can guide me in doing my work.	1	2	3	4	5	6	7
TC7	There is an understandable sequence of steps that can be followed in doing my work.	1	2	3	4	5	6	7
TC8	I can actually rely on established procedures and practices in doing my work.	1	2	3	4	5	6	7

15. Below are the basic functions of BI tools. Please how often you have been using these basic functions. I use more basic features of the BI tool such as:

No	Statements	Never	Very rarely	Rarely	Occasionally/ Sometimes	Often	Very often
RU1	Running existing reports	1	2	3	4	5	6
RU2	Executing existing queries	1	2	3	4	5	6
RU3	Performing basic analysis	1	2	3	4	5	6
RU4	Extracting data from BI tools and preparing reports in Excel	1	2	3	4	5	6
RU5	Accessing standard reports	1	2	3	4	5	6
RU6	Running ad-hoc reporting	1	2	3	4	5	6
RU7	Abstraction of raw data	1	2	3	4	5	6
RU8	Cleansing data	1	2	3	4	5	6

16. Below are the advanced features of BI tools. Please indicate how often you regularly use more advanced features of your BI tool. I use advanced features of the BI tool such as:

No	Statements	Never	Very rarely	Rarely	Occasionally/ Sometimes	Often	Very often
IU1	Self-service tools	1	2	3	4	5	6
IU2	Interactive visualization	1	2	3	4	5	6
IU3	Predictive analytics reports	1	2	3	4	5	6
IU4	Drill down functions	1	2	3	4	5	6
IU5	Creating dashboards	1	2	3	4	5	6
IU6	Constructing my own queries	1	2	3	4	5	6
IU7	Setting performance management targets	1	2	3	4	5	6
IU8	Trend analysis	1	2	3	4	5	6
IU9	Scenario planning	1	2	3	4	5	6
IU10	Predictive modelling	1	2	3	4	5	6
IU11	Agile visualizations	1	2	3	4	5	6
IU12	Optimization	1	2	3	4	5	6

Thank you for your participation.

APPENDIX B: PARTICIPATION INVITATION LETTER AND INDIVIDUAL USE INSTRUMENTS W2

Part A: Demographic Information

Participation Invitation Letter (Individual use) (Wave 2)

Good day,

My name is Thanyani Norman Mudau, and I am a Doctoral student in accountancy at the University of the Witwatersrand (WITS), Johannesburg. As a degree requirement at WITS, I am conducting a study on the use and impact of Business Intelligence (BI) Systems. The purpose of the study is to investigate the factors influencing the innovative use of BI systems by individuals in the management accounting context in South Africa and the impacts of such use of BI systems on management accountant's individual performance. BI systems are defined as information systems software that is used for the purpose of gathering, managing, analysing, and sharing information about external and internal environment to gain insights for better decision making.

As a user of your organisation's BI system you are invited to take part in this study by completing this questionnaire. The questionnaire deals with your perceptions about your use of the BI system and its impact on your performance. Your response is important and there are no right or wrong answers. This survey is both **confidential and anonymous**. **Anonymity and confidentiality** are guaranteed by not needing to enter your name on the questionnaire. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the survey at any stage. The study will be conducted over three stages (waves) 12 weeks apart. This is to allow the researcher to measure BI system use over a period. However, participants do not have to participate in all three stages and participation in each stage is voluntary. This is the first survey and invites all BI system users irrespective of the number of years using the BI tool.

The first part of the survey captures some demographic data, by selecting the appropriate response. The second part of the survey comprises 32 statements. Please indicate the extent to which you agree with each statement, by ticking in the appropriate box. The entire survey should take between 10 to 20 minutes to complete. The survey was approved by the Wits Human Research Ethics Committee (HREC Non-Medical), Protocol Number: H17/04/22.

Should you have any questions, or wish to obtain a copy of the results of the survey in aggregate form, please contact me on +27 82 611 7131 or at mudauno@yahoo.com.
My supervisor's names and email addresses: Prof Jason Cohen- Jason.cohen@wits.ac.za
:Prof Elmarie PapaGeorgiou-Elmarie.Papageorgiou@wits.ac.za

Thank you for considering your participation

Kind regards,
Thanyani Norman Mudau
Faculty of commence, law and management
School of Accountancy
University of the Witwatersrand (WITS), Johannesburg

The Survey is divided into <u>two sections</u>
Part A: Demographic information
Part B: BI system use

This section asks questions about your demographic information including your experience.

The survey is divided into two section

1. Please select your age

18-24	
25-29	
30-35	
36-40	
41-45	
46-50	
51-55	
56 >	
Prefer not to say	

2. Please select your gender

Female	
Male	
Prefer not to say	

3. Please select your years of experience in management accounting within your current organisation.

<2 years	
2-5 years	
6-9 years	
10-15 years	
16-19 years	
>20 years	

4. Please select your years of experience in management accounting within your current organisation.

<2 years	
2-5 years	
6-10 years	
11-15 years	

16-20 years	
>21 years	

5. Please select your total years of experience using BI systems

<2 years	
2-5 years	
6-10 years	
11-15 years	
16-20 years	
>21 years	

6. Please select the BI system you currently use in your role as a management accountant within your organisation.

None	
SAP business object	
Oracle Hyperion	
SAS	
Oracle	
Microsoft	
MicroStrategy	
IBM Cognos	
Qlikeview	
SAGE	
Sisense	
Sybase IQ	
ASYST	
Synergy	
Clear Analytics (Excel based)	
Other (please specify)	

7. Please select your total years of experience using BI systems with your current organisation.

None	
<1 years	
1-2 years	
3-5 years	
6-9 years	
>10 years	

8. Please select if you have attended any formal training programme on BI system use.

Yes	
No	
Prefer not to say	

9. Please select the industry sector, in which you are working as a management accountant.

Manufacturing	
Utilities and energy	
Logistics	
Retail	
Telecom	
Airline	
Pharmaceutical	
Public sector	
Service	
Finance	
Mining	
Accounting	
Other (please specify)	

10. Which of the following best describes your management level?

Junior	
Entry management	
Middle Management	
Senior Manager	
Specialist	
Executive management	
Other (please specify)	

11. Please select your professional membership(s).

CIMA	
SAICA	
Other (please specify)	

12. Please indicate the following in order to facilitate the matching of responses across subsequent waves of the survey while retaining your anonymity.

Items	
State your month of birth (i.e. January)	
State first three letters of your mother's first name	

Part B: Perceptions and Use of BI System

The purpose of this section is to obtain your perceptions about your BI system use.

13. Please indicate the extent in which you agree with each of the following statements related to the BI system that you currently use in your work as a management accountant. Please indicate whether you Strongly disagree, Mostly disagree, Disagree, are Neutral, Agree, Mostly agree or Strongly Agree with each statement.

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
US1	I enjoy using the BI system	1	2	3	4	5	6	7
US2	I would recommend the BI system to other management accountants	1	2	3	4	5	6	7
US3	The BI system works the way I want it to work	1	2	3	4	5	6	7
US4	It is pleasant to use the BI system	1	2	3	4	5	6	7
US5	Overall, I am satisfied with BI system	1	2	3	4	5	6	7
IP 1	Using the BI system improves my job performance	1	2	3	4	5	6	7
IP 2	Using the BI system increases my work productivity	1	2	3	4	5	6	7
IP 3	Using the BI system enhances my effectiveness in my job	1	2	3	4	5	6	7
IP 4	Using the BI system improves my decision-making quality	1	2	3	4	5	6	7
IP 5	Using the BI system helps me to identify potential problems faster.	1	2	3	4	5	6	7
IP 6	Using BI system assist me in making decisions quicker	1	2	3	4	5	6	7
IP 7	Using BI system assist me to spend less time in meetings	1	2	3	4	5	6	7

14. Below are the basic functions of BI tools. Please how often you have been using these basic functions. I use more basic features of the BI tool such as:

No	Statements	Never	Very rarely	Rarely	Occasionally/ Sometimes	Often	Very often
RU1	Running existing reports	1	2	3	4	5	6
RU2	Executing existing queries	1	2	3	4	5	6
RU3	Performing basic analysis	1	2	3	4	5	6
RU4	Extracting data from BI tools and preparing reports in Excel	1	2	3	4	5	6
RU5	Accessing standard reports	1	2	3	4	5	6
RU6	Running ad-hoc reporting	1	2	3	4	5	6
RU7	Abstraction of raw data	1	2	3	4	5	6
RU8	Cleansing data	1	2	3	4	5	6

15. Below are the advanced features of BI tools. Please indicate how often you regularly use more advanced features of your BI tool. I use advanced features of the BI tool such as:

No	Statements	Never	Very rarely	Rarely	Occasionally/ Sometimes	Often	Very often
IU1	Self-service tools	1	2	3	4	5	6
IU2	Interactive visualization	1	2	3	4	5	6
IU3	Predictive analytics reports	1	2	3	4	5	6
IU4	Drill down functions	1	2	3	4	5	6
IU5	Creating dashboards	1	2	3	4	5	6
IU6	Constructing my own queries	1	2	3	4	5	6
IU7	Setting performance management targets	1	2	3	4	5	6
IU8	Trend analysis	1	2	3	4	5	6
IU9	Scenario planning	1	2	3	4	5	6
IU10	Predictive modelling	1	2	3	4	5	6
IU11	Agile visualizations	1	2	3	4	5	6
IU12	Optimization	1	2	3	4	5	6

Thank you for your participation.

APPENDIX C: PARTICIPATION INVITATION LETTER AND INDIVIDUAL USE INSTRUMENTS W3

Section A: Demographic Information

Participation Invitation Letter (Individual use) (Wave 3)

Good day,

My name is Thanyani Norman Mudau, and I am a Doctoral student in accountancy at the University of the Witwatersrand (WITS), Johannesburg. As a degree requirement at WITS, I am conducting a study on the use and impact of Business Intelligence (BI) Systems. The purpose of the study is to investigate the factors influencing the innovative use of BI systems by individuals in the management accounting context in South Africa and the impacts of such use of BI systems on management accountant's individual performance. BI systems are defined as information systems software that is used for the purpose of gathering, managing, analysing, and sharing information about external and internal environment to gain insights for better decision making.

As a user of your organisation's BI system you are invited to take part in this study by completing this questionnaire. The questionnaire deals with your perceptions about your use of the BI system and its impact on your performance.

Your response is important and there are no right or wrong answers. This survey is both confidential and anonymous. Anonymity and confidentiality are guaranteed by not needing to enter your name on the questionnaire. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the survey at any stage. The study will be conducted over three stages (waves) 12 weeks apart. This is to allow the researcher to measure BI system use over a period of time. However, participants do not have to participate in all three stages and participation in each stage is voluntary. This is the first survey and invites all BI system users irrespective of the number of years using the BI tool.

The first part of the survey captures some demographic data, by selecting the appropriate response. The second part of the survey comprises 32 statements. Please indicate the extent to which you agree with each statement, by ticking in the appropriate box. The entire survey should take between 10 to 20 minutes to complete. The survey was approved by the Wits Human Research Ethics Committee (HREC Non-Medical), Protocol Number: H17/04/22.

Should you have any questions, or wish to obtain a copy of the results of the survey in aggregate form, please contact me on +27 82 611 7131 or at mudauno@yahoo.com.

My supervisor's names and email addresses: Prof Jason Cohen- Jason.cohen@wits.ac.za

:Prof Elmarie PapaGeorgiou-Elmarie.Papageorgiou@wits.ac.za

Thank you for considering your participation

Kind regards,
Thanyani Norman Mudau
Faculty of commence, law and management
School of Accountancy
University of the Witwatersrand (WITS), Johannesburg

The Survey is divided into <u>two sections</u>
Part A: Demographic information
Part B: BI system use

This section asks questions about your demographic information including your experience.

The survey is divided into two section

1. Please select your age

18-24	
25-29	
30-35	
36-40	
41-45	
46-50	
51-55	
56 >	
Prefer not to say	

2. Please select your gender

Female	
Male	
Prefer not to say	

3. Please select your years of experience in management accounting within your current organisation.

<2 years	
2-5 years	
6-9 years	
10-15 years	
16-19 years	
>20 years	

4. Please select your years of experience in management accounting within your current organisation.

<2 years	
2-5 years	
6-10 years	
11-15 years	

16-20 years	
>21 years	

5. Please select your total years of experience using BI systems

<2 years	
2-5 years	
6-10 years	
11-15 years	
16-20 years	
>21 years	

6. Please select the BI system you currently use in your role as a management accountant within your organisation.

None	
SAP business object	
Oracle Hyperion	
SAS	
Oracle	
Microsoft	
MicroStrategy	
IBM Cognos	
Qlikeview	
SAGE	
Sisense	
Sybase IQ	
ASYST	
Synergy	
Clear Analytics (Excel based)	
Other (please specify)	

7. Please select your total years of experience using BI systems with your current organisation.

None	
<1 years	
1-2 years	
3-5 years	
6-9 years	
>10 years	

8. Please select if you have attended any formal training programme on BI system use.

Yes	
No	
Prefer not to say	

9. Please select the industry sector, in which you are working as a management accountant.

Manufacturing	
Utilities and energy	
Logistics	
Retail	
Telecom	
Airline	
Pharmaceutical	
Public sector	
Service	
Finance	
Mining	
Accounting	
Other (please specify)	

10. Which of the following best describes your management level?

Junior	
Entry management	
Middle Management	
Senior Manager	
Specialist	
Executive management	
Other (please specify)	

11. Please select your professional membership(s).

CIMA	
SAICA	
Other (please specify)	

12. Please indicate the following in order to facilitate the matching of responses across subsequent waves of the survey while retaining your anonymity.

Items	
State your month of birth (i.e. January)	
State first three letters of your mother’s first name	

Part B: Perceptions and Use of BI System

The purpose of this section is to obtain your perceptions about your BI system use.

13. Please indicate the extent in which you agree with each of the following statements related to the BI system that you currently use in your work as a management accountant. Please indicate whether you Strongly disagree, Mostly disagree, Disagree, are Neutral, Agree, Mostly agree or Strongly Agree with each statement.

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
US1	I enjoy using the BI system	1	2	3	4	5	6	7
US2	I would recommend the BI system to other management accountants	1	2	3	4	5	6	7
US3	The BI system works the way I want it to work	1	2	3	4	5	6	7
US4	It is pleasant to use the BI system	1	2	3	4	5	6	7
US5	Overall, I am satisfied with BI system	1	2	3	4	5	6	7
IP 1	Using the BI system improves my job performance	1	2	3	4	5	6	7
IP 2	Using the BI system increases my work productivity	1	2	3	4	5	6	7
IP 3	Using the BI system enhances my effectiveness in my job	1	2	3	4	5	6	7
IP 4	Using the BI system improves my decision-making quality	1	2	3	4	5	6	7
IP 5	Using the BI system helps me to identify potential problems faster.	1	2	3	4	5	6	7
IP 6	Using BI system assist me in making decisions quicker	1	2	3	4	5	6	7
IP 7	Using BI system assist me to spend less time in meetings	1	2	3	4	5	6	7

14. Below are the basic functions of BI tools. Please how often you have been using these basic functions. I use more basic features of the BI tool such as:

No	Statements	Never	Very rarely	Rarely	Occasionally/ Sometimes	Often	Very often
RU1	Running existing reports	1	2	3	4	5	6
RU2	Executing existing queries	1	2	3	4	5	6
RU3	Performing basic analysis	1	2	3	4	5	6
RU4	Extracting data from BI tools and preparing reports in Excel	1	2	3	4	5	6
RU5	Accessing standard reports	1	2	3	4	5	6
RU6	Running ad-hoc reporting	1	2	3	4	5	6
RU7	Abstraction of raw data	1	2	3	4	5	6
RU8	Cleansing data	1	2	3	4	5	6

15. Below are the advanced features of BI tools. Please indicate how often you regularly use more advanced features of your BI tool. I use advanced features of the BI tool such as:

No	Statements	Never	Very rarely	Rarely	Occasionally/ Sometimes	Often	Very often
IU1	Self-service tools	1	2	3	4	5	6
IU2	Interactive visualization	1	2	3	4	5	6
IU3	Predictive analytics reports	1	2	3	4	5	6
IU4	Drill down functions	1	2	3	4	5	6
IU5	Creating dashboards	1	2	3	4	5	6
IU6	Constructing my own queries	1	2	3	4	5	6
IU7	Setting performance management targets	1	2	3	4	5	6
IU8	Trend analysis	1	2	3	4	5	6
IU9	Scenario planning	1	2	3	4	5	6
IU10	Predictive modelling	1	2	3	4	5	6
IU11	Agile visualizations	1	2	3	4	5	6
IU12	Optimization	1	2	3	4	5	6

Thank you for your participation.

APPENDIX D: PARTICIPATION INVITATION LETTER AND ORGANISATIONAL STUDY INSTRUMENTS

Section A: Demographic Information

Participation Invitation Letter (Organisational use)

Good day,

My name is Thanyani Norman Mudau, and I am a Doctoral student in Accountancy at the University of the Witwatersrand (WITS), Johannesburg. As a degree requirement at WITS, I am conducting a study on the use and impact of Business Intelligence (BI) Systems. The study focuses on South African organisations using BI systems. BI systems are defined as information systems software that is used for the purpose of gathering, managing, analysing, and sharing information about external and internal environments to gain insights for better decision making.

As a person responsible for the use of the BI system in your organisation's management accounting function, you are invited to take part in this study by completing this questionnaire. This questionnaire deals with your perceptions towards the use and impacts of BI systems. The purpose of the study is to examine the extent to which organisational adoption of BI systems impacts on a balanced set of organisational performance measures both directly and indirectly through impacts on the sophistication of management control systems.

Your response is important and there are no right or wrong answers. This survey is both **confidential and anonymous**. **Anonymity and confidentiality** are guaranteed by not needing to enter your name on the questionnaire. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the survey at any stage.

The first part of the survey captures some demographic data about your organisation. The second and third part of the survey comprises 80 statements. Please indicate the extent to which you agree with each statement, by selecting the appropriate response. The entire survey should take between 10 to 20 minutes to complete. The survey was approved by the Wits Human Research Ethics Committee (HREC Non-Medical), Protocol Number: H17/04/22.

Should you have any questions, or wish to obtain a copy of the results of the survey in aggregate form, please contact me on +27 82 611 7131 or at 968384@students.wits.ac.za.

My supervisor's names and email addresses: Prof Jason Cohen- Jason.cohen@wits.ac.za
:Prof Elmarie PapaGeorgiou-Elmarie.Papageorgiou@wits.ac.za

Thank you for considering your participation

Kind regards,

Thanyani Norman Mudau
Faculty of commence, law and management
School of Accountancy
University of the Witwatersrand (WITS), Johannesburg

The Survey is divided into <u>three sections</u>
Part A: Demographic information
Part B: Adoption of BI system
Part C: Financial and non-financial performance

This section asks questions about your demographic information including your experience.

The survey is divided into three section

1. Please select the number of years your company has been using its BI system.

<100	
101-499	
500-999	
1000-4999	
5000-9999	
>10000	

2. Please indicate the revenue that your organisation generates per annum.

<R20 million	
R21-R50 million	
R51-R100 million	
R101-R150 million	
R151-R200 million	
R201-R499 million	
>R500 million	

3. Please select the industry sector in which your organisation operates.

Manufacturing	
Utilities and energy	
Logistics	
Retail	
Telecom	
Airline	
Pharmaceutical	
Public sector	
Service	
Finance sector	
Mining	
Other (please specify)	

4. Please select your job title.

Chief Financial Officer	
Management Accountant	
Finance Director	
Managing Director	
Executive Director	
Other (please specify)	

5. Please select your years of experience in the organisation.

<5 years	
6-10 years	
11-15 years	
> 16 years	

6. Please indicate the number of years that your company has been in operation.

<5 years	
6-10 years	
11-15 years	
16-20 years	
21-25 years	
26-30 years	
31-35 years	
> 36 years	

Part B: Adoption of BI system

The purpose of this section is to obtain your opinion on the extent to which your organisation has adopted BI systems.

7. Please indicate the extent in which you agree with each of the following statements related to the BI system that you currently use in your organisation and the extent which it supports various organisational functions.

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
AD1	Our BI system is supporting financial management	1	2	3	4	5	6	7
AD2	Our BI system is supporting supply chains and procurement	1	2	3	4	5	6	7
AD3	Our BI system is supporting production/service management	1	2	3	4	5	6	7
AD4	Our BI system is supporting project management	1	2	3	4	5	6	7
AD5	Our BI system is supporting human resources	1	2	3	4	5	6	7
AD6	Our BI system is supporting sales	1	2	3	4	5	6	7
AD7	Our BI system is supporting marketing	1	2	3	4	5	6	7
AD8	Our BI system is supporting call centre operations	1	2	3	4	5	6	7

8. Please select the number of years your organisation has been using its BI system.

<1 year	
1-2 years	
3-5 years	
6-9 years	
>10 years	

9. Please select the BI system you currently using in your organisation

None	
SAP business object	
Oracle Hyperion	
SAS	
Oracle	
Microsoft	
MicroStrategy	
IBM Cognos	
Qlikeview	
SAGE	

Sisense	
Sybase IQ	
ASYST	
Synergy	
Clear Analytics (Excel based)	
Other (please specify)	

10. Please select your best estimate of the percentage of your organisation's business processes supported by the BI system.

0% (none)	
1-25% (very few)	
26-50% (some)	
51-75% (most)	
76-100% (almost all)	

11. Please indicate the extent in which you agree with each of the following statements related to your organisational management team, board, environment, strategy and structure.

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
QB1	Our board monitors organisational performance.	1	2	3	4	5	6	7
QB2	Our board accounts to stakeholders on organisational performance.	1	2	3	4	5	6	7
QB3	Our board holds executive management accountable.	1	2	3	4	5	6	7
OE1	Changes in the external business environment make our products/services quickly obsolete.	1	2	3	4	5	6	7
OE2	Changes in the external business environment make our technologies quickly obsolete.	1	2	3	4	5	6	7
OE3	Changes in the external business environment make our competitive practices quickly obsolete.	1	2	3	4	5	6	7
OE4	The business environment is threatening the survival of our organisation.	1	2	3	4	5	6	7
OE5	Tough price competition is threatening the survival of our organisation.	1	2	3	4	5	6	7
OE6	Our competitors' product/service quality threatens the survival of our organisation.	1	2	3	4	5	6	7
ST1	Our organisation provides a variety of products or services.	1	2	3	4	5	6	7

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
ST2	Our organisation makes frequent changes to products/services that it offers.	1	2	3	4	5	6	7
ST3	Our organisation is a pioneer attempting to be first in introducing innovative products/services.	1	2	3	4	5	6	7
ST4	Pricing below competitors is a constant emphasis for us.	1	2	3	4	5	6	7
ST5	Continuing, overriding concern for lowest cost per unit is a constant emphasis for us.	1	2	3	4	5	6	7
ST6	Products or services in lower priced market segments is a constant emphasis for us.	1	2	3	4	5	6	7
OS1	Our workers have the authority to correct problems when they occur.	1	2	3	4	5	6	7
OS2	Our work teams have control over their job.	1	2	3	4	5	6	7
OS3	Our supervisors or middle managers are supportive of the decisions made by our work teams.	1	2	3	4	5	6	7
OS4	We encourage workers to be creative in dealing with problems at work.	1	2	3	4	5	6	7

Part C: Financial and Non-Financial Performance

The purpose of this section is to obtain your opinion on your organisation's performance and its management control systems.

12. Please indicate the extent in which you agree with each of the following statements related to how the organisation has performed relative to the expectation it has set for itself.

No	Statements	Much worse than expected	Worse than expected	Somewhat worse than expected	Neutral	Somewhat better than	Better than expected	Much better than expected
NBP1	Business process performance has been____	1	2	3	4	5	6	7
NBP2	Effectiveness of business process monitoring has been ____	1	2	3	4	5	6	7
NBP3	Business process continuous improvement has been______	1	2	3	4	5	6	7
NBP4	Efficiency of internal processes has been___	1	2	3	4	5	6	7
NBP5	Staff productivity has been____	1	2	3	4	5	6	7
NBP6	Decision making has been___	1	2	3	4	5	6	7
NCR1	Customer satisfaction has been___	1	2	3	4	5	6	7
NCR2	Response time to customers has been___	1	2	3	4	5	6	7
NCR3	Customer retention has been___	1	2	3	4	5	6	7
NCR4	Time to market for our products/services has been_____	1	2	3	4	5	6	7
NOL1	Employee satisfaction has been____	1	2	3	4	5	6	7
NOL2	Success in employees testing new ideas has been_____	1	2	3	4	5	6	7
NOL3	Employee training has been______	1	2	3	4	5	6	7
NOL4	Number of new products/services launched has been_____	1	2	3	4	5	6	7
FP1	The increase in operating income has been___.	1	2	3	4	5	6	7
FP2	The improvement in sales growth rate has been___	1	2	3	4	5	6	7
FP3	The increase in return on investment has been___	1	2	3	4	5	6	7
FP4	The increase in return on assets has been___	1	2	3	4	5	6	7
FP5	Increase in gross profit has been___	1	2	3	4	5	6	7
FP6	The reduction in operating cost has been___	1	2	3	4	5	6	7

13. Please indicate the extent in which you agree with each of the following statements related to how the BI system is contributing to management reporting:

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
MR1	Our BI system ensures that data included in control reports are very precise	1	2	3	4	5	6	7
MR2	Our BI system produces control reports that contain data useful for management	1	2	3	4	5	6	7
MR3	Using our BI system, managers can closely monitor trends between last period's actual results and the results of the current period	1	2	3	4	5	6	7
MR4	Our BI system monitors virtually all tasks in the organisation	1	2	3	4	5	6	7
MR5	Our BI system allow for frequent reporting of control information to senior managers	1	2	3	4	5	6	7
MR6	Our BI system provides control reports with a sufficient level of detail for senior managers	1	2	3	4	5	6	7
MR7	Our BI system produces control reports relating to outputs produced with inputs consumed	1	2	3	4	5	6	7
MR8	Using our BI system, managers can closely compare actual results with those of competitors in the same industry	1	2	3	4	5	6	7
MR9	Our BI system provides managers with budget reports that show changes between current year results and the results of previous years.	1	2	3	4	5	6	7
MR10	Our BI system includes external data about industry developments	1	2	3	4	5	6	7
MR11	Our BI system produces control reports that suit differing individual needs.	1	2	3	4	5	6	7

14. Please indicate the extent to which your sophistication organisation's formal management control system has performed relative to expectation.

No	Statements	Much worse than expected	Worse than expected	Somewhat worse than expected	Neutral	Somewhat better than	Better than expected	Much better than expected
SFC1	Contribution of our cost control systems (such as variance analysis) to organisational performance outcomes	1	2	3	4	5	6	7
SFC2	Contribution of our strategic planning systems to organisational performance outcomes	1	2	3	4	5	6	7
SFC3	Contribution of our budget systems to organisational performance outcomes	1	2	3	4	5	6	7

No	Statements	Much worse than expected	Worse than expected	Somewhat worse than expected	Neutral	Somewhat better than	Better than expected	Much better than expected
SFC4	Contribution of our activity-based costing systems to organisational performance outcomes	1	2	3	4	5	6	7
SFC5	Contribution of our result monitoring systems to organisational performance outcomes	1	2	3	4	5	6	7
SFC6	Contribution of our internal auditing systems to organisational performance outcomes	1	2	3	4	5	6	7
SFC7	Contribution of our external auditing systems to organisational performance outcomes	1	2	3	4	5	6	7
SFC8	Contribution of our forecast systems to organisational performance outcomes	1	2	3	4	5	6	7
SFC9	Contribution of our production/service control systems to organisational performance outcomes	1	2	3	4	5	6	7
SFC10	Contribution of our external scanning systems to organisational performance outcomes	1	2	3	4	5	6	7

15. Please indicate the extent in which you agree with each of the following statements related to the sophistication of your organisation's informal management control systems.

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
SIC1	We are satisfied with how our employees can achieve consensus seeking without needing management intervention	1	2	3	4	5	6	7
SIC2	We are satisfied with how our employees can participate in decision making	1	2	3	4	5	6	7
SIC3	We are satisfied with how our employees can practice open channels of communication	1	2	3	4	5	6	7
SIC4	We are satisfied with how our employees can adapt to the local situation	1	2	3	4	5	6	7
SIC5	We are satisfied with how our managers can share information with colleagues across the organisation	1	2	3	4	5	6	7
SIC6	We are satisfied with how our corporate culture encourages informal signalling of potential problems	1	2	3	4	5	6	7
SIC7	We are satisfied with how our managers can develop new ideas even if they fall outside an individual area of responsibility	1	2	3	4	5	6	7

No	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
SIC8	We are satisfied with how our top-level managers can co-ordinate business activities across the organisation	1	2	3	4	5	6	7
SIC9	We are satisfied with how our employees can work towards targets without needing management intervention	1	2	3	4	5	6	7

Thank you for your participation.

APPENDIX E: EXPLORATORY INTERVIEWS

Sample Participation Invitation Letter (Interviews)

Good day,

My name is Thanyani Norman Mudau, and I am a Doctoral student in accounting science at the University of the Witwatersrand (WITS), Johannesburg. As a degree requirement at WITS, I am conducting a study on the use and impact of Business Intelligence (BI) Systems. The study focuses on the individual management accountants in South Africa. *BI systems are thus defined as information systems software that is used for the purpose of gathering, managing, analysing and sharing information about external and internal environment to gain insights for better decision making.*

As a user of BI system, you are invited to take part in this study by answering this interview questionnaire. There are no right or wrong answers. This questionnaire deals with your perceptions towards the use and impacts of BI systems. The purpose of the study is to investigate the factors influencing the innovative use of BI systems by individuals in the management accounting context and the impacts of such use of BI systems on management accountant's individual performance.

Your response is important and there are no right or wrong answers. This interview is both confidential and anonymous. Anonymity and confidentiality are guaranteed by not needing to enter your name on the questionnaire. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the interview at any stage. The interview is conducted to refine the research instruments. This will allow the researcher to finalise the research instruments.

Please answer the interview questions in your own words. The entire interview should take between 10 to 20 minutes to complete. The interview was approved by the Wits Human Research Ethics Committee (HREC Non-Medical), Protocol Number: Number: H17/04/22.

Should you have any questions, or wish to obtain a copy of the results of the survey in aggregate form, please contact me on +27 82 611 7131 or at mudauno@yahoo.com.
My supervisor's names and email addresses: Prof Jason Cohen- Jason.cohen@wits.ac.za
:Prof Elmarie PapaGeorgiou-Elmarie.Papageorgiou@wits.ac.za

Thank you for considering your participation

Kind regards,
Thanyani Norman Mudau
Faculty of commence, law and management
School of Accountancy
University of the Witwatersrand (WITS), Johannesburg

Interview Schedule

The use and impact of Business Intelligence systems in Management Accounting: an Empirical Study in the South African Context

Interview Questions

- Please describe the main features of your BI system that you use?
- Which of these features are advanced and routine?
- How would you define advanced and routine use of a BI system?
- What factors influence the satisfaction with the BI system?
- What factors enable or constrain the extent to which they can use more BI system features to support their work.

APPENDIX F: ETHICAL CLEARANCE

Research Office

HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)
R14/49 Mudau

CLEARANCE CERTIFICATE	**PROTOCOL NUMBER: H17/04/22**
PROJECT TITLE	The use and impact of business intelligence systems in management accounting: An empirical study in the South African context
INVESTIGATOR(S)	Mr T Mudau
SCHOOL/DEPARTMENT	Accountancy/
DATE CONSIDERED	21 April 2017
DECISION OF THE COMMITTEE	Approved Permission letters are required before data collection can commence
EXPIRY DATE	7 August 2020

DATE 8 August 2017 **CHAIRPERSON** pp (Professor J Knight)

cc: Supervisor : Professor J Cohen

DECLARATION OF INVESTIGATOR(S)

To be completed in duplicate and **ONE COPY** returned to the Secretary at Room 10004, 10th Floor, Senate House, University. Unreported changes to the application may invalidate the clearance given by the HREC (Non-Medical)

I/We fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to resubmit the protocol to the Committee. **I agree to completion of a yearly progress report.**

Signature

10 / 08 / 2017
Date

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES

APPENDIX G: T TEST NON-RESPONSE BIASED

Individual Use Study Chapter 6					
T-Test for Non-Response Biased of Early and Late Respondents					
Constructs	Mean		T-test	Sig. (2-tailed)	Mean Difference
	Early (within 1st 5 days) N=54	Late (last 5 days) N=65			
System Quality	5,645	5,481	0,883	0,381	0,164
Data Quality	5,531	5,660	-0,753	0,455	-0,130
Information Quality	5,659	5,550	0,594	0,555	0,108
Service Quality	5,526	5,400	0,756	0,453	0,126
User Satisfaction	2,941	3,144	-0,744	0,460	-0,204
Individual Performance	6,026	6,140	-1,138	0,260	- 0,114
System Efficacy	3,858	3,488	1,641	0,107	0,370
Task complexity	5,829	6,065	-1,384	0,172	-0,236
Routine Use	4,977	4,826	0,878	0,384	0,150
Innovative Use	5,551	5,659	-1,150	0,255	-0,108

Organisational Use Study Chapter 8					
T-Test for Non-Response Biased of Early and Late Respondents					
Constructs	Mean		T-test	Sig. (2-tailed)	Mean Difference
	Early (within 1st 5 days) N=32	Late (last 5 days) N=26			
Adoption of BI system	6,082	5,981	0,455	0,653	0,102
Quality of the board	4,949	5,103	-0,522	0,606	-0,154
Organisational environment	4,897	5,122	-0,581	0,566	-0,224
Strategy	5,923	5,808	0,435	0,667	0,115
Organisational structure	4,962	4,731	0,504	0,618	0,231
Business process	4,854	4,671	0,569	0,574	0,183
Customer	4,385	4,712	-0,844	0,407	-0,327
Organisational learning	4,346	4,362	-0,034	0,973	-0,015
Financial performance	4,062	4,092	-0,216	0,831	-0,031
Management Reporting	4,215	4,852	-1,940	0,064	-0,636
Sophistication of formal control	5,008	4,746	1,302	0,205	0,262

Organisational Use Study Chapter 8					
T-Test for Non-Response Biased of Early and Late Respondents					
Constructs	**Mean**		**T-test**	**Sig. (2-tailed)**	**Mean Difference**
	Early (within 1st 5 days) N=32	**Late (last 5 days) N=26**			
Sophistication of in-formal control	5,487	5,295	0,770	0,448	0,192