BUSINESS INTELLIGENCE IMPLEMENTATION: AN EVALUATION OF ITS IMPACT ON THE QUALITY OF DECISION-MAKING IN JORDAN'S MINING SECTOR

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Abstract

Within the literature, it has been stressed that the popular business intelligence system (BIS) is a key form of information system (IS) that provides decision-makers with actionable and insightful real-time information to help enhance the organisational performance through more effective decision-making. Nowadays, in the context of the market growth of BISs, the mining sector in Jordan has begun to embrace the implementation of such systems, which are perceived to be necessary for supporting decision-making, and thereby leveraging competitive advantage. As per myriad systems that are organisation-wide, BISs are complex and their implementation can be challenging, with the risk that the measures of expected success may fail to be met. Problems in implementation can be multifarious, including the determination of which business processes and content should be included, which technologies are appropriate for the organisational needs, how business intelligence (BI) is to be integrated within the existent systems, and how to manage the organisational culture to promote change and acceptance. Currently, research for the determination of the key factors contributing to success in the implementation of BI is limited. Furthermore, there is a lack of research related to understanding success in BI implementation within developing countries, the Middle East and North Africa (MENA) in general, and in Jordan in particular. The existing gap is addressed by this study, which aims to identify those implementation factors that have an impact on BI success within the Jordanian mining sector, so that a suitable BI implementation success model can be developed for that particular sector. An extensive review of literature was undertaken, enabling a conceptual framework to be developed based on previous studies, the identified implementation factors and theories of success for ISs. For this research, a positivist philosophy was adopted with a deductive approach and quantitative method that utilised a web-based questionnaire survey to acquire quantitative data for the testing and validation of the proposed framework. A total of 372 valid instruments were received from a sample of managers working within the Jordanian mining sector. SPSS (v.25) was employed in the analysis of the demographic statistics, while AMOS (v.25) was utilised in testing the measurement model through confirmatory factor analysis, and for testing the structural model via structural equation modelling; both of these demonstrated a good fit to the data, with good construct validity. The findings showed that BIS success was affected by a number of implementation factors: business plan and vision, management support, champions, resources, IT infrastructure, attitudes toward technology, project management, data source systems and user participation. Moreover, this research has confirmed that system quality impacts significantly upon information quality, while information quality also impacts significantly upon decision quality. In addition, the results indicated that BIS quality has a mediating influence in the relationship between information quality resulting from the system of BI and the implementation factors. Furthermore, the results showed that the information quality provided from the BIS has a mediating influence on the relationship between decision quality and system quality. This study progresses the body of literature in terms of i) investigating implementation factors that impact BI success within the mining sector in Jordan, ii) evaluating BI and IS success, iii) assessing the relationships of mediation amongst implementation factors that are associated with success in BISs, and iv) proposing a BI implementation model for the mining sector in Jordan. Moreover, this research makes a contribution and has particular relevance for decision-makers and practitioners seeking strategies for the improvement of success in BISs. The study offers guidance with regard to key implementation factors for BI, is convincing with regard to the value of BI and encourages its use within decision-making in order to ensure a positive impact on the quality of the decisions made.

Declaration

I declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Signed:

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List of Abbreviations

AGFI	Adjusted Goodness-of-Fit Index
ANOVA	Analysis of variance
APC	Arab Potash Company
ATT	Attitudes toward Technology
AVE	Average Variance Extracted
BI	Business Intelligence
BIS	Business Intelligence System
BPV	Business plan and vision
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CH	Champion
CHM	Change Management
CR	Composite Reliability
CSF	Critical Success Factor
DOI	Diffusion of Innovation
DQ	Decision Quality
DSS	Data Source Systems
GDP	Gross Domestic Product
GCI	Global Competitiveness Index
GEI	Global Entrepreneurship Index
GFI	Goodness-of-Fit Index
GII	Global Innovation Index
GOI	Global Opportunity Index
ICT	Information and Communication Technology
IFI	Incremental Fit Index
IMF	International Monetary Fund
IS	Information System
IT	Information Technology
ITI	Information Technology Infrastructure
IQ	Information Quality
JPMC	Jordan Phosphate Mines Company
JDOS	Jordanian Department of Statistics

MENA	Middle East and North Africa
MI	Modification Index
MS	Management Support
NFI	Normed Fit Index
PM	Project Management
R	Resources
RMSEA	Root Mean Square Error of Approximation
SD	Standard Deviation
SEM	Structural Equation Modelling
SPSS	Statistical Package for Social Sciences
SQ	System Quality
T	Trust
TAM	Technology Acceptance Model
TS	Team Skills
TLI	Tucker–Lewis Index
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TTF	Task Technology Fit
UP	User Participation
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
WTO	World Trade Organisation

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Chapter One:

Introduction

1.1 Introduction

Chapter 1 presents an introduction to this particular PhD research for the development of a business intelligence system (BIS) implementation model focused on the implementation factors that have a bearing on the success of the BIS and that will lead towards the enhanced quality of decisions in the mining sector in Jordan. The chapter comprises six distinct sections. Section 1.2 presents a background of the topic in general, an outline of the research problem and the key research question. Then, the chapter focuses on the Jordanian research context in section 1.3, with a deeper focus on the mining sector in Jordan. The study rationale, and the aim and objectives of the research are put forward within section 1.4 and section 1.5, respectively. Finally, in section 1.6, an overview of the thesis structure is provided.

1.2 The background and the research problem

For many centuries, the global mining sector has played a role that has become increasingly important, both directly and indirectly, within socio-economic development (Bryceson et al., 2013). According to a study undertaken in 2019 by the World Economic Forum, mineral utilisation can be traced as far back as the seventeenth century for the most dynamic nations, industries and inventions. Meanwhile, it has been reported that there is increasing pressure on manufacturers to take more responsibility for their utilisation of minerals and to transform towards greater sustainability (World Economic Forum, 2019). Within the context of Jordanian mining, the area of information systems (ISs) is one that requires the utmost attention (Al Tarawneh, 2016). If the growth, profitability and survival of an organisation is to be assured, it is vital that information of a high quality is made available for the right people when they require it (Williams and Williams, 2007). Generally, organisations have vast amounts of data in their possession; however, much of it is of poor quality or inappropriate, regardless of whether there has been a large investment in new forms of information technology (IT) (Williams and Williams, 2007). BISs do, however, offer the potential for delivering significant volumes of information that is accurate, timely, presented intelligently and ultimately of use; consequently, decision-making can be enhanced considerably by BISs (Yeoh and Koronios, 2016).

Nowadays, many companies of various size and within a broad range of industrial sectors have been implementing BISs to support their decision-making and the improvement of organisational performance—sectors where BISs have been implemented range from healthcare and manufacturing, to financial services (Kappelman et al., 2019). Indeed, it has been estimated that global revenues from the implementation of BIS reached a total of US$ 21.6 billion in 2018, representing an increase of 11.7% from 2017 (Gartner, 2019). It is believed that there will be further interest in such solutions and further adoption in the future. In fact, for several years BIS implementation was amongst the top four initiatives of IT investment within business organisations (Grand View Research, 2019). Organisations may acquire several benefits from the implementation of BI in projects. A BIS can help organisations to arrive at well-informed business decisions, and thus can be a contributory factor in helping a business gain a competitive advantage within its sector (Ranjan, 2009). Furthermore, BI may be useful in the case of specific requirements to enhance managers' abilities to make decisions in an organisation (Isik et al., 2013). Moreover, a BIS can cover of broad range of technologies and techniques employed in the gathering of data, the provision of access to data, and the analysis of data from various sources so that more effective decisions can be made (Delen and Demirkan, 2013). Furthermore, BI can improve upon the quality and timeliness of information, and lead to enhanced communication between departments with greater coordination of activities, thereby enabling companies to respond more quickly to changes in customer preference, operations within the supply chain and financial circumstances. According to Ranjan (2009), for those companies utilising BI, there is an overall improvement in performance.

Whilst there does appear to be widespread acceptance and usage of BI amongst leading organisations across the world, there have been few studies undertaken that conducted an investigation of the factors that have an impact on BI implementation success (Yeoh and Popovič, 2016). The suggestion is raised within the literature that there are several factors that could be significant in that regard, such as the project champion, the qualities of top management and the strategy, and so on; however, there appears to be little-to-no commonly held agreement amongst authors as to what those factors might be (Yeoh and Popovič, 2016; Dooley et al., 2017; García and Pinzón, 2017; Nasab et al., 2017). Generally, most studies that have involved the exploration of these issues have been undertaken within developed countries such as the United States or those in western Europe, while studies conducted within developing countries are rare or limited (Bakunzibake et al., 2016). A country that is termed ‘developing’ is one that has a standard of living that is low, with an industrial base that is relatively undeveloped and a Human Development Index that is moderate to low (Brown and Thompson, 2011). Jordan can be considered a country that is developing, although it has growing levels of expertise related to business practice and new technology application, and further insights from the experience of Jordan could be beneficial for other countries within the MENA region (World Economic Forum, 2019). Furthermore, amongst those nations, Jordan provides an example of success in its experience of reform programmes and growth within numerous sectors such as education, mining and healthcare (Elsheikh and Hijjawi, 2016). Therefore, this particular study has the aim of empirically identifying and testing those factors that could have an impact on BI implementation success, through the use of approaches from multiple perspectives, in order to address the existent gap in understanding and knowledge in regard to that issue. Furthermore, although the study focuses on the mining sector within Jordan, it could be argued that a degree of generalisation from the results could be possible to enable application in other Jordanian industries, and for other countries within the region that feature similar cultural traits. So that the research problem can be explored, one key research question will form the focus for this study:

> What are the factors contributing to the successful implementation of business intelligence systems in the Jordanian mining sector?

1.3 The study context

1.3.1 Jordan: An overview

Jordan is known officially as the Hashemite Kingdom of Jordan (Al-Mamlakah al-Urduniyyah al-Hashimiyyah). The country is an Arabic nation that is situated within the Middle East and shares borders with Saudi Arabia to the south and east, Palestine to the west, Iraq to the north-east and Syria to the north. Amman is the capital city, and the total land area of the country is approximately 92,300 km^2 (329 km^2 relating to inland bodies of water and 91,971 km^2 related to land) (Library of

Congress, 2006). In accordance with the 1952 constitution, the Jordanian government system is a parliamentary one that has a hereditary monarchy. In terms of demographics, Jordan has a total population of approximately 10 million people (Jordan Department of Statistics, 2018). Of that population, around 98% are Arabs, with the remaining 2% split between minority groups of Chechens, Armenians and Circassians. The most commonly used language, which is also the official one for the country, is Arabic; however, there is wide understanding of English amongst the educated upper and middle classes (Jordan Department of Statistics, 2018).

The vast majority of people in Jordan are Muslim (~93%), while the largest religious minority is composed of Christians, who comprise approximately 5% of the population; other small religious communities make up the remaining population of around 2% (Library of Congress, 2006). The Jordanian Department of Statistics (JDOS) has estimated that the rate of literacy in the country in 2018 stood at 94.9% overall, with 92.8% for women and 96.9% for men (Jordan Department of Statistics, 2018). This achievement is noteworthy when it is considered that the average literacy rate for the region is slightly below 80% (The World Bank, 2018). The estimated labour force of Jordan in 2015 was around 2.5 million workers (Jordan Department of Statistics, 2018), with the official rate of unemployment estimated to be 18.6% in 2018.

Jordan is only a small country with limited resources with respect to water and agriculture, and with deficiencies in resources to supply domestic energy that have been hampering economic development and hindering improvements in living standards. However, in recent years, greater efforts have been made by the government to highlight the positive economic attributes of the country, such as the skilled and well-educated workforce, and the political stability in comparison with many neighbouring countries (Jordan Department of Statistics, 2018). Since King Abdullah succeeded to the throne in 1999, attempts have been made by the government to undertake broad economic reforms that have a strong emphasis on privatisation and economic liberalisation. As such, the previous heavy involvement of the state within the economy has been diminished to a degree, and the private sector has grown (Library of Congress, 2006). This newfound commitment to economic growth (fuelled by private investment) and macroeconomic stability is quite a departure from Jordan's earlier economic history. In the main, due to increased government subsidies and spending, double-digit rates of inflation were experienced as recently as 1989, along with severe currency devaluation, persistently high budget deficits and considerably increases in the national debt. However, from 1989 to 2004, readjustment programmes supported by the International Monetary Fund (IMF) were closely adhered to by the government; there were six such programmes that proved successful in reducing the deficit, controlling inflation and achieving more sustainable growth. Those reforms, working in tandem with an improved political standing internationally, have enabled Jordan to enter into a number of key free-trade agreements with markets such as the European Union and the United States, as well as to become a member of the World Trade Organisation (WTO) (Library of Congress, 2006; The World Bank, 2018).

Despite its economic successes in recent years, there is still considerable economic fragility in Jordan with relatively high unemployment and poverty levels, along with instability that is endemic for the region as a whole. The country is classified by the World Bank as having a 'lower middle-income'. The economy is still overwhelmingly dominated by services and, even though there has been recent growth within the manufacturing sector, such advances could be undermined by looming Asian competition (Library of Congress, 2006; The World Bank, 2018). The economic resource-base for Jordan primarily involves potash, phosphates and their fertiliser derivatives. There is also a dependency upon foreign aid, overseas remittances and tourism, which are the basic sources of hard currency. The Jordanian dinar (JD or JOD) is the national currency. In September 2019, the exchange rate for one US dollar was JOD 0.71. Jordan's gross domestic product (GDP) was US$ 42.231 billion in 2018, representing 0.07% of the global economy. For the 1976–2018 period, Jordan's average GDP was US$ 14.4 billion, reaching its highest level of US$ 42.231 billion in 2018, compared to US$ 1.7 billion in 1976 (The World Bank, 2018).

Jordan became a member of the WTO on the 11th of April 2000 (World Trade Organisation, 2016). Since 1952, Jordan has actively participated in World Bank activities and those of the IMF. With several indices across the world, Jordan is also considered a leading member of the MENA region. Several indices serve as significant indicators of Jordan's performance in financial and economic terms, including the Global Opportunity Index (GOI), the Global Innovation Index (GII), the Global Competitiveness Index (GCI) and the Global Entrepreneurship Index (GEI). Indeed, in the case of the GEI, Jordan has a current ranking of 70th out of a total of 141 countries (World Economic Forum, 2019). Moreover, in the category related to labour market flexibility, Jordan has its best performance with a global ranking of 26th position. Those ranking-related attributes result from wage flexibility, a multi-skilled workforce, prolific utilisation of information and communication-related technologies (i.e. information and communication technology [ICT]), the institutional capacities within the nation, the encouragement of labour migration between countries, business sophistication, an environment that is flexible and fosters flexible working, proficient markets and a high degree of soundness in macroeconomic terms. In respect to the GCI pillars, the ranking for Jordan in the financial system is the 33rd position, 45th for health, 46th for institutions, 58th for skills, 61st for the product market, 64th for innovation capability, 74th for infrastructure, 80th for market size, 82nd for the adoption of ICT, 84th for the labour market, 88th for business dynamism, and 111th for macroeconomic stability.

Progress made with regard to rankings can be attributed to initiatives taken to strengthen the product market, especially in terms of improvements to the degree of market dominance, as well as a prevalence for tariff-free imports. Jordan does, however, require greater flexibility with regard to its innovation capability so that the efficient use of innovation can be ensured (World Economic Forum, 2019). Furthermore, Jordan had a 2018 ranking of 49th with respect to entrepreneurial ecosystems amongst the GEI (Global Entrepreneurship and Development Index, 2018), which places Jordan above 63% of the countries within the index, including Hungary (50th), South Africa (55th), Malaysia (58th), Azerbaijan (62nd) and Russia (78th). As with other indices, Jordan also leads the MENA region with respect to the taking of a different strategic approach towards global integration and engagement (Global Entrepreneurship and Development Index, 2018). From a total of 129 different countries, Jordan is placed 86th within the GII index, and thus ahead of Tajikistan, Paraguay and a number of other countries within MENA such as Algeria, Egypt, Lebanon and Yemen. In respect to innovation, Jordan has been placed amongst the top 70 countries from across the world for several years. The GII framework considers innovation to have a more horizontal and generic nature with the inclusion of technological and social innovations, as well as that found within business models. The ranking for the sub-index of innovation input for Jordan is 91st place, while the ranking for the sub-index of innovation output is higher at the 71st position. That slightly higher score for Jordanian innovation output in comparison with input indicates that there is efficiency within the country with respect to innovation. Nevertheless, increased innovation inputs would result from further improvements to the institutions, market and business sophistication, research and human capital, and infrastructure. The results will impact output pillars including technology, knowledge and creative outputs, which the Innovation Efficiency Index confirms with a ranking for Jordan of 79th (The Global Innovation Index, 2019). This reveals that Jordan has average efficiency in terms of utilising its inputs of innovation for the realisation of enhanced innovation outputs. Furthermore, such a rank within the most recent of years leads to calls for serious consideration of how the national systems of innovation are managed and coordinated.

1.3.2 Information and communication technology within Jordan

ICT is essential within IS development for an organisation. A broad collection of communications and information processing technologies are encompassed within ICT, and it is emphasised that a significant feature of IS is telecommunication technology (Wallace, 2015). ICT was defined by Peña-Lopez (2009) as a set of diverse resources and technological tools that are employed in the transmission, storage, creation, sharing or exchanging of information. Those resources and technological tools may include technologies for live broadcasting (e.g. webcasting, television and radio), techniques for recorded broadcasting (e.g. video and audio players, storage devices and podcasting), computers, the internet (e.g. email, blogs and websites) and various forms of telephony (e.g. satellite, mobile, fixed and video-conferencing). Rapid shifts in technology are now commonplace, and so there is now potential for ISs to enable access from multiple platforms including tablets, laptops, desktop computers and various mobile devices. Since ICT development and its contribution is in a constant state of flux, there is also an ongoing need for new assessments of impact (Walsham, 2017); however, ICT development within developing countries has typically been focused on capacity for the export of software services and products, rather than a focus on the potential contribution that

ICTs could make to IS innovation domestically (Oosterlaken, 2012). Therefore, the conclusion can be drawn that ICTs constitute effective mechanisms for transforming the services of government and meeting particular stakeholder demands, as well as those of the public in general. Furthermore, ICTs play a significant role within the development, implementation and maintenance of government ISs.

As the ICT sector in Jordan has the potential to become a key driver of economic growth, since the early years of the twenty-first century there has been robust expansion in telecoms and an agenda of liberalisation within the country in order to support internet usage and rapid growth in the penetration of mobile telephony. The Jordanian ICT sector has seen a recent focus on a series of government reforms that have targeted support for growth in macroeconomic terms, with new programmes of lending and multiple incentives related to taxation that have provided support to firms working in the technology sector and to service providers of IT (Oxford Business Group, 2018). Recent strategies of development have identified multiple lines of ICT business that offer considerable opportunities for private sector investment with the ongoing drive for digitisation and e-government services expected to be supportive to growth in the private sector which, consequently, is expected to enable sustainable development over the long term and the eventual transformation of the economy into one that is knowledge-based (Oxford Business Group, 2018). The volume of investment within Jordanian ICT enterprises is four times the Middle East region average: approximately US$ 500 for each US$ 1 million of GDP in comparison to the US$ 120 regional average.

It has been stressed that the ICT sector of Jordan presents opportunities for increased competitive advantage in relation to other Arab region countries. Indeed, it has been highlighted that the investment volume for the sector totals approximately US$ 199 million, whilst the ICT exports of the Kingdom within the last year rose to a total of US$ 324 million. In respect to employment, it has been noted that there are around 18,000 workers who are directly employed within the ICT sector, with a total of 1,839 new ICT graduates in 2016 (Prieto, 2018; World Economic Forum, 2018). The ICT sector has played a significant role in the economic growth of Jordan and its IT market has become one of the region’s fastest growing. Together with this rapid rise in the IT sector, the Jordanian economy has transformed, along with its image, from being slow-moving and low on technology to one that is high-tech, with many innovative entrepreneurial workers. There continues to be improvement in the competitiveness and economic stabilisation within the country with respect to the provision of IT-related services, such that the total revenue from IT services in 2017 was US$ 681,710,762 (Intaj, 2017). In recent years, the sector has continued to evolve with the focus primarily placed on the installation of infrastructure and IT hardware, the development of software, the sale of software licences, the wholesale of infrastructure and IT hardware, the wholesale of telephones and telecommunications equipment, and the installation of telecommunications equipment and wireless services for telecommunications. The revenue from IT industry exports has yielded US$ 268,577,218, and US$ 413,133,545 in domestic revenue. In recent decades, the top Jordanian IT companies have emerged as global leaders within the IT sector and have contributed to technological growth in Jordan, and in the global market in general, ultimately having a transformative effect on the Jordanian economy (Intaj, 2017).

1.3.3 The Jordanian mining industry

The mining industry in Jordan is comprised of domains related to both extraction and manufacturing (Energy and Minerals Regulatory Commission, 2018). The entities that have the most prominence deal in phosphate, potash and cement. As such, it is imperative that those characteristics intrinsic to the mining of such products are appreciated within any frameworks of regulation (Alnawefleh et al., 2013). These particular products contribute 80% of the entire industry’s revenues, and so their activities are indicative of where the strengths in the sector lie. Other minerals that are prominent include oil, limestone, kaolin and bromate. In the years between 2004 to 2014, the contribution of the mining sector increased from 10.5% to 15% of Jordanian GNP (Al Tarawneh, 2016; Jordan Department of Statistics, 2018), with the sector continuing to actively promote foreign direct investment for the government. According to a government report for 2014, the mining sector contributed approximately 3% of the GDP (Jordan Department of Statistics, 2014), while in 2016 the sector continued to play an influential role in economic growth.

Within the Jordanian extraction industries there are over 60 organisations with around 10,000 employees, and approximately 191,000 workers within branches of manufacturing. Whilst Jordan does have extensive capacity for producing shale oil, the country continues to expend the majority of its annual revenues on the importing of energy-related products from other countries such as Egypt (Taib, 2013). The mining industry in Jordan is predominantly related to the production of potash and phosphate, and since independence in 1946, those minerals have significantly contributed to economic development, notwithstanding the considerable variability in exports during that period (Al Rewashed and Maxwell, 2013). Besides potash and phosphates, there is also the mining of smaller quantities of other minerals such as copper ore, unrefined salt, manganese ore, gypsum and the precursors of ceramic production (i.e. clays, feldspar and glass sand) (Library of Congress, 2006; Jordan Department of Statistics, 2018). Nevertheless, phosphates and potash remain the key economic exports for the country.

The Jordanian Arab Potash Company (APC) was established in 1956 as a Pan-Arab venture, and is now the 8th largest producer of potash globally based on production volume (Arab Potash Company, 2018). In 2018, the APC's production of potash was approximately 1.2 million tons, which translated into sales revenue of around US$ 320 million, making potash the second most lucrative good for export. Moreover, with the total level of production in 2005 being approximately 6.4 million tons, Jordan was the third largest raw phosphate producer in the world (Arab Potash Company, 2018; Jordan Department of Statistics, 2018). The Jordan Phosphate Mines Company (JPMC) is a limited company of public shareholding that was established in 1949 for the mining and processing of phosphate ore within Jordan. Over the last six decades, JPMC has evolved into a key pillar of the Jordanian economic structure and a key exporter, positioned as a pioneer amongst international companies operating in the mining and fertiliser-production domains. JPMC's activities may be classified within two kinds of complementary sectors: mining and the manufacturing of phosphate fertiliser. With its integration of these sectors, JPMC has proven its capability within the international markets. The production activities of the company are operational within Jordan, which has the fifth largest phosphate reserves in the world; the Jordanian reserves equate to approximately 3.75 billion tons, with approximately 1.25 billion tons of the reserves located within JPMC's mines. As such, the company is the second largest exporter and sixth largest producer of phosphate internationally, and has production capacity that exceeds 7 million tons of phosphates annually (Jordan Phosphate Mines Company, 2018). In recent years, BI has been introduced within many organisations operating in the Jordanian mining sector (Arab Potash Company, 2018; Realsoft, 2018). A number of organisations went on to implement a packaged system of software (e.g. Microsoft and Oracle), whilst others invested in local BI development such as BIS for technical support, namely the APC Portal that was implemented in 2013 (Realsoft, 2018).

1.4 The study rationale

Implementation factors for successful BI project implementation have been addressed in previous research (Wixom and Watson, 2001; Xu and Hwang, 2007; Arnott, 2008; Hwang and Xu, 2008; Yeoh and Koronios, 2010; Woodside, 2011; Işık et al., 2013; Audzeyeva and Hudson, 2016; Hung et al., 2016; Yeoh and Popovič, 2016; Puklavec et al., 2017; El-Adaileh and Foster 2019); however, there is still a need for improvement to BI implementation as several such projects have continued to fail or not fulfil their full potential (Yeoh and Popovič, 2016; García and Pinzón, 2017). It is thus essential that the implementation factors that impact on BI success are identified. Moreover, this study aims to gain an understanding of the effect that implementation factors have on the system of BI and the quality of information that can enhance the decision-making process quality. Furthermore, there has been limited research undertaken within the BI implementation field in Jordan. Indeed, it is noted that nearly all the previous research within the field has been conducted in developed country contexts. This author has identified a paucity of studies to have investigated the issues associated with BI project implementation within developing countries, and the MENA region in particular. Moreover, it is considered that there is a lack of research of an empirical nature to examine the implementation factors impacting upon BIS success within developing countries in general, and within Jordan in particular, and no research has been undertaken to date with a focus on those implementation factors that impact on BI project success within the mining sector in Jordan.

It is believed that the undertaking of this study within Jordan, itself a developing country, has the potential to yield results that are significant and that can serve to bridge the gaps identified for this research area. The rationale for the selection of the mining sector in Jordan as the context of the research is multifaceted. Firstly, the sector of mining is a domain that makes a significant contribution to the

Jordanian economy and provides much employment. Secondly, BISs are recognised as having growing importance for improving the quality of decision-making. Mining firms' focus on their decision support systems (e.g. BI) has considerably enhanced the decision quality and led to an overall improvement in organisational performance. Furthermore, another aspect worthy of consideration is the partial or full implementation of BI within the systems of the Jordanian mining sector. Therefore, in order for the practicality of BI implementation in the Jordanian mining sector to be addressed, this study establishes the aim and objectives presented within the following section.

1.5 The study aim and objectives

The aim of this study is to advance knowledge and understanding of the implementation of BI, the factors that influence that implementation's success, and how BI impacts upon the quality of decision-making in the Jordanian mining sector.

Following on from the study's aim, the following five objectives are formulated:

1. Identifying the implementation factors that affect BI success
2. Assessing the BI implementation factors in the Jordanian mining sector
3. Testing the impact of the implementation factors on BI success
4. Analysing the mediating impact of the system and the information quality of BI implementation success
5. Developing and validating a conceptual framework that defines the impact of successful BI implementation on the quality of decision-making in the context of the Jordanian mining sector

1.6 The thesis structure

Seven chapters serve for the presentation of this thesis, with an outline of each chapter provided below.

- **Chapter 1** provided the research outline, the motivation behind undertaking the research, the study background, the establishment of the aim and objectives of the research.
- **Chapter 2** features a comprehensive literature review in relation to IS and BI, with consideration given to their definitions, their evolution and the associated theories. Similarly, consideration is also given to decision quality, while the chapter highlights the gaps identified within the reviewed literature.
- **Chapter 3** presents comprehensive analyses and discussions in relation to the development of a theoretical framework, with the emphasis placed on those theories that support the study's aim and objectives. The chapter conducts a detailed review and analyses of the various models for implementation, and those theories linked to the success of BI and IS. The various implementation factors that impact on the success of BI are discussed within the chapter in order to introduce a basis for the conceptual framework's development. Finally, the chapter develops the hypotheses put forward for the study.
- **Chapter 4** includes further details with regards to the research philosophy, as well as the research design and research methods employed in the collection and analysis of the data. Within the chapter, there is also a description of the development of the scales of measurement and the study population, as well as a discussion surrounding the selection of the sample. Furthermore, rationales are given for the data analysis procedures and techniques, and those ethical considerations that have relevance for the study.
- **Chapter 5** contains the presentation of the empirical data analysis associated with the conceptual framework. The data analysis is comprised of the results of the data analysis of the descriptive statistics, followed by a description of the respondents' profiles. The chapter presents the findings related to the testing of the validity of the constructs through confirmatory factor analysis.

Moreover, testing is carried out in relation to the structural model through the structural equation modelling technique.

- **Chapter 6** features a discussion of the findings presented within Chapter 5 in comparison to studies explored in the literature review. The results are interpreted in order to fulfil the study's aim and objectives.
- **Chapter 7** provides a conclusion for the thesis, outlining its performance in terms of addressing the objectives of the research. Moreover, there is discussion of the study's theoretical, practical and economic contributions. Finally, there is acknowledgement of the limitations of the study, and suggestions made for future research.

Chapter Two: The Literature Review

2.1 Introduction

This chapter conducts a comprehensive literature review in relation to ISs and BI. Consideration is given to the evolution, theories and definitions of IS and BI, while an attempt is made to secure a sound working definition to act as a guide for the work undertaken in this research. There is a general consideration of ISs, and a more specific exploration of BI with an examination of the current debates and its implications for decision-making quality. In addition to this introduction, the chapter is composed of five sections. Within section 2.2 that follows, there is discussion of the discipline of IS and studies that relate to its implementation. Furthermore, it is important for there to be recognition of those theories that are applicable to the research question, and so this section also includes an examination of the specific theories related to successful IS implementation, as well as consideration of why those theories might have relevance in terms of achieving the objectives of this research. Section 2.3 places its lens of focus on BISs by presenting an overview, definitions, their evolution and the value in successful BI implementation. Section 2.4 then considers the definition and measurement of decision quality, why it has importance, as well as placing particular emphasis on decision-making quality in relation to the degree of effectiveness for successful BI. Then, section 2.5 features an overview of the current debate related to the implementation of BI, with identification of the existing gaps within the literature. Finally, section 2.6 presents the conclusions drawn from this literature review through a summary of the chapter.

2.2 Information systems

Typically, traditional organisations may need to confront issues such as insufficient reporting, a lack of information or knowledge, or even a data overflow. Therefore, since a decision should be made promptly within the shortest time period possible to keep pace with a situation, it is common for high management levels to make decisions that are based on experience (Stair and Reynolds, 2018). However, this can lead to the decision value itself being lowered, and an increased risk of failure in the decision outcome (Wallace, 2015; Stair and Reynolds, 2018). With the maturation of competition globally, the traditional approaches to decision-making are no longer able to satisfy the organisational requirements for efficiency and consequent benefits. Therefore, companies must take advantage of the utilisation of electronic tools so that useful information can be extracted promptly from huge data volumes through the provision of skills to enable the making of fast decisions (Laudon and Laudon, 2017). In the context of yet another tranche of IS, organisations cannot avoid the topic of the promotion of IS solutions for addressing issues from the level of operations to the level of decision-making (Stair and Reynolds, 2018). The IS that is applied in an organisation ought to be capable of demonstrating information or data accurately and in real-time, so that processing and consequent decision-making can be expedited in a timely manner (Kucukaltan et al., 2016).

Various definitions for IS have been put forward since it is an embodiment of a multiplicity of concepts. Beginning with a broad definition, IS is defined by Gasser (1986) as comprising software, hardware, networks of communication, information or data, participants or people, and work processes or procedures. Symons (1991) considers IS to be a system that utilises computer software and hardware, models for analysis, manual procedures, planning, decision-making, a database and control. Land (1985), however, places emphasis on the social aspects within his IS definition, stating that it is:

> A social system, which has embedded in it, IT. The extent to which IT plays a part is increasing rapidly. But this does not prevent the overall information system from being a social system, and it is not possible to design a robust, effective information system, incorporating significant amounts of the technology without treating it as a social system.
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> (Land, 1985, p. 215)

IS is described by Alter (1999) as being a system that has human participants performing business processes through the use of hardware, software and information in order to capture, store, retrieve, transmit, display and/or manipulate information for either external or internal customers. Thus, IS can be considered to include a human dimension along with the hardware, software, information and all the types of technology for the creation, storage and exchange of information in various ways. ISs are defined by Iivari (2005) as systems that are computer-based and offer users information in relation to specific topics within certain organisational contexts. Meanwhile, Lyytinen and Newman (2006, p. 4) describe them as being an “organizational system that consists of technical, organizational and semiotic elements which are all re-organized and expanded during ISD (IS development) to serve an organisational purpose”.

Wallace (2015, p. 395) refers to IS as being "A system that brings together four critical components to collect, process, manage, analyse, and distribute information". The four components introduced are as follows. Firstly, people are critical irrespective of the various roles that they can play in relation to IS such as visionary, developer or manager; or as an analyst, customer, user, contributor or someone who liaises with regard to IS; or, on occasion, a 'roadblock' (Wallace, 2015). As Petter and McLean (2009) note, people play an essential role in whether most ISs succeed or fail. Secondly, there is the technological aspect to IS including the software, hardware and the telecommunications (Wallace, 2015). The third aspect noted by Wallace (2015) relates to the processes that are perceived as sets of activities that are designed for the achievement of tasks, with organisations proceeding with the implementation of an IS in order to streamline, support and occasionally eliminate certain business processes. The fourth aspect is the data, which is seen as the pieces of information or individual facts that are converted into a digital format that facilitates their integration within an IS for computer programs to read, and for sharing across systems (Wallace, 2015).

There is a plethora of literature within the IS domain that merges the realms of technology and business (Chiasson and Davidson, 2005). Business researchers explore the relationships amongst business modelling, business processes, IT management, IT governance and IT portfolio management (Claver et al., 2001). The technological domain encompasses those areas of research related to methodology, design and analysis, development, security, implementation and deployment (Walsham and Sahay, 2006). Research studies of IS also vary in relation to their application such as knowledge management systems, decision support systems, database management systems, executive support systems, transaction processing systems, accounting systems, BISs, health systems, transaction processing systems, and manufacturing systems, amongst many others (Walsham and Sahay, 2006; Laudon and Laudon, 2017). Each area of IS research has its own groups or followers who sometimes cross over into other domains. As such, it can be difficult for IS research areas to be streamlined. This study has been devised to only place its lens of focus upon the implementation of IS, particularly in relation to BI-related systems. In the following section, consideration is given to theories related to the implementation of IS and their success. It is considered imperative for this study to reiterate that a primary intention is to discover which factors impact on success BI implementation. Therefore, in order for the extent of failure or success in the implementation of systems to be checked, consideration has been given to the issue of how to evaluate implementation and success in relation to IS.

2.2.1 Information system implementation

IS development requires a structured approach for the processes involved. The development of the system occurs throughout the IS project lifecycle from the planning stage right through a number of different phases until the system is implemented (Wallace, 2015). There are numerous models for the lifecycle of the development of systems that warrant investigation, and whilst they may have different emphases within their slightly different approaches, the various IS development lifecycle models all tend to follow certain processes and guidelines (Wixom and Watson, 2001; Beynon-Davies et al., 2004; Lapointe and Rivard, 2007; Hung et al., 2010; Anjariny and Zeki, 2013; Yeoh and Popovič, 2016; Puklavec et al., 2017). A traditional model for the development lifecycle for systems encompasses a sequence of seven steps: planning, analysis, design, development, testing, implementation and maintenance. Within this study, a focus is placed on the stage of implementation, which is considered to be the process through which the financial, organisational and technical resources are configured in order to provide an operational and efficient system (Fleck, 1994). Although there has been investigation of the IS implementation field for many years, there is still inadequate progress in terms of understanding the implantation of IS (Lapointe and Rivard, 2007; Arvidsson et al., 2014; Davis and Yen, 2018). As the building, testing and analysing of a framework that is comprehensive in covering all IS lifecycle aspects would have been beyond the capabilities of any one researcher, the intention of this study is the provision of empirical evidence related to the framework of implementation.

Research into IS implementation has been classified by Kwon and Zmud (1987) into five groups—political research, process research, prescriptive research, mutual understanding research and factor research—which will now be briefly considered. Political research addresses the various interests of users within the implementation of IS. Kwon and Zmud (1987) assert that for implementation to be successful there is a need for diverse interests to be both addressed and managed. Studies within this area can vary in perspective from that of the users, the managers, the key users and various other stakeholders (McAfee, 2002; Ho et al., 2017; Xin and Choudhary, 2019). The presumption can be made that various user groups will have contrasting expectations and interests, and that there can also be a diverse variety of interests between countries, organisations or even departments of the same organisation (Ho et al., 2017). A major drawback with this kind of research is the difficulty in creating a research model or framework that is generic and applicable for the domain of IS because the subject matter is of such an extensive nature (Kaul and Joslin, 2018). Process research places its focus on activities of social change, utilises many theories of organisational change (Kwon and Zmud, 1987; Cooper and Zmud, 1990), and has the goal of understanding the overall process of implementation so that it may be managed effectively. This kind of research perceives the efforts at implementation as being within a sequential series of stages or events that vary in number within different studies, and thus the definitions for the stages of implementation are inconsistent (Law and Ngai, 2007). Process research is more complete and thorough when compared to the other kinds, as every implementation process aspect is covered; however, the research area remains limited as the evaluation and inspection of all the implementation stages, as well as the lack of standardisation for the number of stages to be considered, leads to complexity (Ika et al., 2012).

Meanwhile, prescriptive research emphasises the identification of factors that are related to the risks of implementation with risk being defined as those potential problems that could hinder the success of IS implementation (Huang et al., 2004). This kind of research has the primary intention of formulating strategies for how organisations could resolve or overcome risk(s) (Schwartz, 2016). The study area does appear to overlap with other kinds of implementation research, particularly the research of factors (Jugdev and Müller, 2005). The emphasis of prescriptive research is placed upon risk factors; however, research on factors is focused on the underlying reasons that have a bearing on whether IS implementation is a failure or a success. Results from both kinds of research appear to be somewhat similar, even though different approaches to the management of results are adopted (Schwartz, 2016). Mutual understanding research explores information exchange and the interactions between system users and system designers. In essence, this kind of research suggests that there is a positive relationship between users and developers that leads to an enhanced probability that implementation will be a success (Kaul and Joslin, 2018). This kind of research was at its most popular in the 1980s and 1990s, when many studies were focused on investigating the involvement of users during the process of implementation (Ives and Olson 1984; Baroudi et al., 1986; Amoako-Gyampah and White, 1993; Torkzadeh and Doll, 1994; Petter et al., 2008; Schwartz, 2016), although methodological and theoretical issues have tended to limit the expansion of this kind of research to some extent (Kwon and Zmud, 1987). Finally, factor research places its emphasis on the identification of organisational, individual, socio-technical, project and technological factors that relate to failures and successes in the implementation of IS (Xin and Choudhary, 2019). There have been numerous criticisms of factor research; for example, Heeks (2017) highlights that i) the approach fails to inform in terms of how implementation factors ought to be implemented, ii) those factors establishing successful implementation tend to differ across different studies, and iii) there can be a further division of success into partial or total success. It is highly challenging, therefore, to determine which factors lead to successful implementation. Furthermore, within factors research, factors are merely listed whereas in the real world, factors tend to overlap with the various relationships amongst them (Jugdev and Müller, 2005; Ika et al., 2012; Mir and Pinnington, 2014; Kaul and Joslin, 2018). Another point made by Ko et al. (2002) is that previous research has failed to explain how the organisation is affected by a list of implementation factors, while many studies lack a clarifying theoretical framework to help appreciate the business outcomes when implementation factors are present or absent.

Amongst the five different research groups related to the implementation of IS, factor research appears to be most appropriate for application within this study in terms of realising the study objectives. The primary challenge for factor research is the determination of definitions for the factors of IS implementation, which can vary depending on the location, time and perspective (DeLone and McLean, 1992; Van den Berg, 2001). Therefore, a clear definition of the implementation factors is important from the outset so they can be investigated throughout the research process. (Section 3.2 in Chapter 3 includes further deliberation of the definition of BI implementation factors employed within this research.) This section has clarified the various kinds of study related to the implementation of IS, as well as the significance of such research to IS implementation. Prior to a discussion of the literature related to BI, numerous pertinent theories of IS success will be considered within the subsequent section that may be employed in developing the conceptual framework.

2.2.2 Theories of information system success

Various theories, models and perspectives have been developed for evaluating IS success within organisations. The literature relating to IS includes numerous developed models that aim to explain IS success and/or user acceptance. The most common models that relate to the evaluation of success in IS implementation include Rogers's (1960) diffusion of innovation, Fishbein and Ajzen's (1975) theory of reasoned action, Ajzen's (1985) theory of planned behaviour, Davis's (1986) technology acceptance model, Goodhue and Thompson's (1995) task-technology fit, Venkatesh et al.'s (2003) unified theory of acceptance and use of technology, and DeLone and McLean's (1992, 2003) IS success model. So that an appropriate theory can be identified for the measurement of IS implementation in this research, the most common models and theories of IS are examined and discussed within the following paragraphs.

- **Diffusion of innovation**

Diffusion of innovation (DOI) was first introduced in the 1960s by Rogers (2003) in order for the dissemination of innovation within society to be studied in a more careful considered fashion. DOI, also known as innovation diffusion theory, passed through various stages of development until Rogers (2003) achieved the optimum version of the model. DOI suggests that an individual's adoption of innovation may be classified into one of five categories based on their degree of innovativeness or in accordance with the time that the new idea first began to be utilised (i.e. whether someone is an innovator, an early adopter, one of the early majority, one of the late majority or a laggard). Rogers notes that the rate of an individual's innovation adoption can be affected by certain innovation attributes (i.e. compatibility, relative advantage, trialability, observability and complexity). The DOI model was developed further by Moon and Benbasat (1991), who gave it new constructs (i.e. visibility, compatibility, voluntariness with regard to use, the ease of use, demonstrability of results, relative advantage, trialability and image) to better establish it within IS research and to improve its ability to measure the perceptions of users towards IT innovations. This theory, however, does not have relevance for this study as there is limited inclusion of the analysis levels of the individual.

- **Theory of reasoned action**

The theory of reasoned action (TRA) was introduced by Fishbein and Ajzen (1975), and is recognised within numerous empirical studies as being a useful model for facilitating the explanation of the behaviours and usage intentions of users. The theory does compare favourably to alternative models such as the technology acceptance model (Venkatesh, 1999; McKnight, Choudhury and Kacmar, 2002). The indication from TRA is that the acceptance of technology is determined by the influence that others have on technology usage (social influence or subjective norm) and the intent one has for utilising the technology (behaviour). The hypothesis of the theory is that the intention of people to use systems can lead to the actual behaviour of system usage. Furthermore, the belief that others may wish for them to begin using a system also increases the likelihood that people will use a system. Ajzen and Fishbein (1980) consider TRA to be an extremely general kind of model that can be appropriately employed for the study and explanation of different human behaviour such as that related to computer usage. It has been acknowledged that TRA has been successful in the explanation and prediction of behaviour models across various domains, with the recognition that it is an intention model that has been well researched (Fishbein and Ajzen, 1975). Nonetheless, TRA has been targeted at gaining an understanding of the intentions of individuals with regard to technology use and does not relate to the organisation. Therefore, it is not suitable for application in this study since it aims to determine a theory applicable for an organisation, a group of individuals or merely an individual.

- **Theory of planned behaviour**

The theory of planned behaviour (TPB) includes an explanatory variable termed 'perceived behavioural control', which refers to the perceived difficulty or ease of performing a behaviour, with the assumption that it reflects past experience in addition to anticipated obstacles and impediments such as receiving an 'A' grade within a course (Ajzen, 1991). If there has been a positive experience of acquiring an 'A' grade in the past, and few obstacles exist to receiving another 'A', there is an increase in perceived behavioural control which, therefore, increases the chances of an 'A' grade being obtained (Ajzen, 1985). In addition to the perceptions of ability, linking the perceived behavioural control of TPB within the IS domain refers to the conditions that facilitate technology (Conner and Sparks, 1996). The likelihood of behaviour oriented towards adoption increases when perceived control is higher and when subjective attitudes and norms are favourable. When individuals discover that they have control with respect to their behaviour, there is more likelihood that they will exploit an opportunity that is presented and execute the associated behaviour, which suggests that the driving force behind a behaviour is the intention (Terry et al., 1999). Expressed another way, factors that are beyond the control of a person with respect to the adoption of technology, such as training and education, are explained by perceived behavioural control. Once again, this particular model is not considered appropriate for use within this research because it is only applicable to individuals.

- **Technology acceptance model**

The technology acceptance model (TAM) was forward by Davis (1986) as a TRA derivative that was fashioned purposefully to generate the acceptance of IT by users. The assertion of TRA theory is that attitudes are swayed by beliefs, that this affects intentions, and finally leads to the generation of behaviours. This relationship of beliefs with attitude and intentions, through to behaviour has been adopted by TAM for the modelling of IT acceptance by users. Taylor and Todd (1995) note that the TAM model identifies those causal relationships that lie between the features of system design, the perceived usefulness, the perceived level of ease of use, the attitudes with regard to the use, and then the actual behaviour with respect to usage (Davis, 1989). TAM has been derived from TRA, which describes the acceptance that individuals have of IS within their computer usage, especially with regard to the use of e-mail (Taylor and Todd, 1995). TAM's goal is providing explanations for the determinants of acceptance of computers that, in general, are capable of explaining the behaviour of users across a wide range of end-user computing technologies and a broad range of user populations, whilst also being both theoretically justified and parsimonious (Davis et al., 1989). There is good acceptance of the TAM model within the research community and, due to its popularity, it has been extended by Venkatesh and colleagues. This has led to the development of the technology acceptance model 2 (TAM2) (Venkatesh and Davis, 2000), the unified theory of acceptance and use of technology (Venkatesh et al., 2003), and the technology acceptance model 3 (TAM3) (Venkatesh and Bala, 2008). Considerable research has utilised and tested the extended models of TAM in order to gain an understanding of technological adoption and diffusion within various organisations worldwide (Szajna, 1996; Agarwal and Prasad, 1998; Gefen et al., 2003; Malhotra et al., 2006; Kijsanayotin et al., 2009; Venkatesh et al., 2011; Venkatesh et al., 2016; Jeyaraj, 2019). Despite TAM evolving along with its various models, it is not considered appropriate for this study as it is only applicable to individuals.

- **Task technology fit**

Goodhue and Thompson’s (1995) theory of task technology fit (TTF) is based on interactions between technology and business processes. It posits that there is likely to be usage of technology, such as a system of enterprise resource planning or BI, if it can support the users’ tasks. There is a likelihood that IT that fail to benefit users will be ignored. Moreover, there is an emphasis of IT integration within this theory as TTF is intended to be applicable to various user rules throughout organisations. The variable of TTF is the main explanatory one for the theory. Nevertheless, the theory is excluded from this study as it only accommodates individual fit.

- **Unified theory of acceptance and use of technology**

Venkatesh et al. (2003) introduced the unified theory of acceptance and use of technology (UTAUT) to predict new technology users’ acceptance. Various models have been utilised for synthesising and reaching a unified perspective on users’ acceptance of technology. Eight models have been reviewed, compared and integrated in order for the UTAUT model to be developed (Venkatesh et al., 2003), including TPB, TRA, DOI and TAM. Venkatesh et al. (2003) view the UTAUT model’s aim as providing further prediction of the behaviours of individuals that it would not be possible to gather and explain through the use of one single model. All of the above- mentioned models utilised in the development of the UTAUT have several independent variables that enable the prediction of the adoption and usage of users. Venkatesh et al. (2003) discovered four different and significant constructs that directly impact on the acceptance of users and their usage behaviour: performance expectancy, social influence, facilitating conditions and effort expectancy. They propose that performance expectancy, effort expectancy and social influence have a direct effect on the behavioural intention of individuals, while facilitating conditions are assumed to impact directly on user behaviour. Furthermore, moderating variables are considered within the UTAUT model and are deemed to have impacts on the behavioural intention of the users and use, namely gender, age, voluntariness of use and experience. The model, however, is not appropriate for use within this study as it is only applicable to individuals.

- **Information system success**

DeLone and McLean’s IS success model offers a comprehensive evaluation of IS success, and hence success may be considered to be a multidimensional variable. Due to that unique characteristic, IS success measurement may involve six interrelated dimensions. The implication of the model is that success in IS may be evaluated in terms of quality (information, service and system) and its impact (organisational, net benefits or individual) (DeLone and McLean 1992, 2003). The theory is amongst the most widely-accepted within the IS literature because of its comprehensive nature (Petter et al., 2008). Given that the primary intention of this study is to conduct an investigation of factors that have an effect on the successful implementation of BIS, the theory is considered suitable for inclusion within the theoretical framework. (Section 3.2, Chapter 3, for a further elaboration of the theory.)

After a comprehensive investigation of the various theories in IS success, and their respective benefits and characteristics, the theoretical study framework for this research will primarily be a combination of the studies on implementation factors and the DeLone and McLean IS success model. The studies and theories on IS are thus combined, as it would be more challenging for the research objectives to be realised through the use of one single theoretical framework. Furthermore, the integration of multiple theoretical frameworks aids in putting forward explanations for complex issues. Further elaboration of the theoretical study framework is provided within Chapter 3.

2.3 Business intelligence

The term ‘business intelligence’ is first thought to have been used in 1958 by Hans Peter Luhn, who was working as a scientist for IBM. The BIS was then defined by Luhn (1958) as an autocratic system developed for the distribution of information to various divisions within any governmental, scientific or industrial organisation; that system of intelligence applied technologies of data processing for the creation of interest profiles related to each ‘action point’ within an organisation (Luhn, 1958). The BI concept was implemented by an analyst called Howard Dresner within the Gartner research group in the late 1980s (Watson and Wixom, 2007), who invented a method for improving a manager’s ability to make improved business decisions through the use of accurate data hailing from a data warehouse (Power, 2007). There was broad acceptance of the concept amongst both academics and practitioners, and since then interest in the BI field has continued to grow. In particular, within the context of research, BI is considered to be an aspect of the systems for decision-making designed to decrease the uncertainty surrounding the process of making decisions (Clark et al., 2007). Further, in more practical terms, organisations began to morph into environments of BI with a singular ‘version of truth’ by using data that was cross-organisational, and which had been provided through integrated architecture (Eckerson, 2003; Negash, 2004). Thus, BI became a significant form of IS that is able to assist organisations in the management, development and communication of intangible resources such as knowledge and information. As a consequence, BI is now considered to be vital for every organisation that operates within the knowledge-based economy (Alnoukari, 2009). The suggestion is that the making of informed decisions is believed to result in improved outcomes. The capability of making informed decisions has been improved by technology through the delivery of systems that support the collection and dissemination of data for decision-makers. In the past thirty years, there has been a continuous evolution of IT systems that have delivered BI to underpin the growth in data availability and the increased appetite of decision-makers for relevant information. Further BI definitions and a brief history of the development of the modern system of BI are provided in the sections that follow.

2.3.1 Defining business intelligence

BI is the area of the IS discipline that has a focus on support for, and the improvement of, managers' decision-making (Arnott and Pervan, 2016). BI is not merely a term representing a collection of techniques and tools; it is a concept that is multi-dimensional, and which Olbrich et al. (2012, p. 4149) notes is "concerned with the effective deployment of organisational practices, processes, and technology to create a knowledge base that supports the organisation". In essence, BISs involve the conversion of structured data into information that is useful for those making decisions through the use of procedures and systems intended to facilitate improved decision-making (Wixom and Watson, 2012). There are a range of definitions for BI within the literature; for instance, Negash (2004, p. 178) defines BISs as being those that are able to "combine data gathering, data storage, and knowledge management with analytical tools to present complex internal and competitive information to planners and decision makers", while Watson (2009, p. 487) characterises BI as "a broad category of applications, technologies, and processes for gathering, storing, accessing, and analysing data to help business users make better decisions". BI is defined by Vitt et al. (2002, p. 13) as "an approach to management that allows an organisation to define what information is useful and relevant to its corporate decision making", with Howson (2007) considering BI as a type of activity that enables people at all organisational levels to gain access to data with the potential to interact and analyse it, so that business can be managed, performance improved, opportunities discovered and operations enhanced to promote greater efficiency. BIs are defined by Golfarelli et al. (2004) as ISs for the processing of information into data and its conversion into knowledge for the facilitation of decision-making, while Loshin (2003) considers BI to represent a set of methodologies and tools that are designed for the exploitation of actionable knowledge that has been discovered from within the information assets of a company.

Davenport and Harris (2007) consider BI to encompass analytics, and comprise a set of processes and technologies that utilise data for gaining further understanding of business performance and to facilitate its analysis, while BI is described by Glancy and Yadav (2011) as a system that transforms data into a variety of informational products, with BI focusing on providing support for a range of business functions through the use of a process approach and advanced analysis techniques. Technology, methods and products are combined by BI for the organisation of key information required by the management in order to improve performance and profit (Williams and Williams, 2007). Generally, BI in the form of business-related information and associated analyses within the context of processes related to key aspects of business leads to decision-making and action that can result in improvements to the performance of a business. Williams and Williams (2007) note in particular that BI involves the leveraging of information assets within key processes of a business so that improved performance can be achieved. BIs involve business information and associated analysis that i) are utilised within a key business process context, ii) are supportive of decisions and actions, and iii) result in improved performance of the business (Williams and Williams, 2007). Another further definition forwarded by Laudon and Laudon (2017) defines BI as a contemporary term describing software tools and data for the organisation, analysis and provision of access to data in order to aid managers and other users within an enterprise to make decisions that are more informed. Furthermore, the decision-making needs are addressed by BI at every management level.

Wallace (2015, p. 197) defines BI as:

> An umbrella term that includes the vast quantities of information an organisation might use for data-driven decision making, from within its own data repositories and also from external sources. The term also encompasses the software applications, technologies, and practices that managers apply to the data to gain insights that help them make better decisions.

Turban et al. (2014, p. 35) describe BI as "An umbrella term that encompasses tools, architectures, databases, data warehouses, performance management, methodologies, and so forth, all of which are integrated into a unified software suite". A data warehouse is a form of technology that is used for storing information within multi-dimensional structures in order for analysis to be facilitated (Aufaure et al., 2013). Nevertheless, several authors have used the 'data warehousing' term to move beyond descriptions for technology types to describe processes that have similarity with BI, and they are frequently covered together in the literature since that data made available within a data warehouse has centrality to the use of the BI tool

(Wixom and Watson, 2001; Arnott, 2008; Adamala and Cidrin, 2011; Boyton et al., 2015; Kfouri and Skyrius, 2016; Owusu et al., 2017). A data warehouse is a central repository for data that contains information drawn from a multiplicity of sources that may be utilised within information gathering, strategic planning and analysis (Wallace, 2015). Sharda et al. (2018) consider that the term 'data warehouse' refers to a kind of physical repository where there is special organisation of relational data for the provision of cleansed data across an enterprise in a standardised format. BI and data warehousing will, for the purposes in this study, be considered synonymous. Based on the literature related to BI, it is defined in this research as a form of IS that serves to combine technology, products and methods with the primary focus placed on the gathering, storage, integration, access, analysis and presentation of data in order to support users in making improved business decisions that can lead to enhanced business performance.

2.3.2 Evolution of business intelligence

By the early 1960s, many aspects of business operations were beginning to be computerised within organisations (Arnott and Pervan, 2016). There was development of IS in order for applications such as billing, order processing, payroll, accounts payable and inventory control to be performed (Arnott and Pervan, 2016). The first ISs had the goal of making information within transaction-processing systems readily available to managers for the purposes of decision-making; however, few of the early ISs achieved success (Ackoff, 1967; Tolliver, 1971). A major factor that led to failure was that the professionals working in IT at that time had failed to fully appreciate managerial work and its demands. The systems developed had a tendency to be inflexible and large, and whilst reports generated from managers' ISs were often several dozen pages long, there was little information of use to the management (Ackoff, 1967; Mintzberg, 1977).

Modern BISs have been developed in the IS context in general, and more specifically in the form of expert systems, executive information system and decision support systems (Williams and Williams, 2007). BISs have been developed as a form of technological solution for the storage, integration and analysis of the information required for supporting decision-making within large organisations

(Popovic et al., 2012). Power (2007) explains that the BIS evolved from the decision support systems that emerged within the 1960s for aiding decision-making and planning. However, prior to the formal recognition of BISs, there was already discussion around the concept. Luhn (1958, p. 314) was the first to describe the ‘business intelligence’ term, employing the definition of intelligence from the Webster’s Dictionary and stating that it described “the ability to apprehend the interrelationships of presented facts in such a way as to guide action towards a desired goal”. Moreover, Luhn (1958) put forward an overview of basic BIS components, many of which can still be recognised today. Finally, he suggested that a system of BI would collect data automatically from a multiplicity of sources and communicate relevant information so that selected data could be provided, allowing problems to be solved.

Following Luhns’s (1958) description for the system of BI, the period from the 1960s to 1980s saw the development of decision support systems in order to assist in planning and decision-making, which were typically utilised for narrowly focused activities such as investment management, transportation applications and production planning. However, as software applications such as the Statistical Package for Social Sciences (SPSS) and the Statistical Analysis System began to be introduced in the 1970s, end users were able to more easily access statistical software to assist in their task completion (Ranjan, 2008). Following on from decision support systems, data warehouses, enterprise resource planning systems and executive support systems began to be developed. Data warehousing and associated querying are most commonly utilised in the monitoring of performance and support for decision-making. Executives utilised executive support systems in order to view performance and they had less focus on support for decision-making. There was no widespread usage of executive support systems due to executives’ resistance to such hands-on usage (Davenport, 2006).

In the 1990s, the modern-day terminology of BI was defined by the Gartner Group as being related to “concepts and methods to improve business decision making by using fact-based support systems” (Power, 2007, p.100). More recently, as market environments have become increasingly complex and the competition between vendors of BISs has grown more intense, the capabilities in modern BIS have been increased by developers and they can now store and synthesise, perform analysis and communicate the insights on the data and information required for better decision-making (Power, 2007; Ranjan, 2008). Modern BISs are now often comprised of a data warehouse utilised for storage, with the capability for extraction and loading for the transformation of raw corporate system data (to prepare the data warehouse for use by employing a range of defined data structures and definitions), an ability for data mining, dashboards for effective communication of data: and analytical tools for the forecasting and development of other insights (Aruldoss et al., 2014). Sherman (2014) points out that the history of BI spans across several decades, with organisations having developed data warehouses that use relational databases for the support of management reporting back in the late 1980s, a considerable period of time before they started to be referred to as 'data warehouses'. Over the interim years, terminology has been created by the industry to describe the current technologies, such as data marts, dimensional models and BI (Sherman, 2014). More recently, BI has become one of the top initiatives within IS according to a variety of industry analyst surveys in relation to chief information officers (Sherman, 2014; Rosenkranz et al., 2017). Regardless of the prevailing economic conditions, there has been rapid growth of BI in comparison to spending on IS overall, as enterprises within a range of industries consider BI to be a necessary strategic element for operations and growth (Sherman, 2014; Pagoropoulos et al., 2017). In many respects, BI has maturity; however, it would be a significant overstatement to equate that with a sense of stagnancy or stodginess (Sherman, 2014). As shown in Figure 2.1 below, the market for BI has experienced sustained innovation throughout its history. Each new wave of innovation has unleashed new powers for increased capabilities in analysis, followed soon after by further demands for greater insights and more data (Sherman, 2014). Figure 2.1 offers an explanation for the innovation within numerous categories of technology that have provided support for BI and the integration of data through databases, enterprise applications and technology platforms.

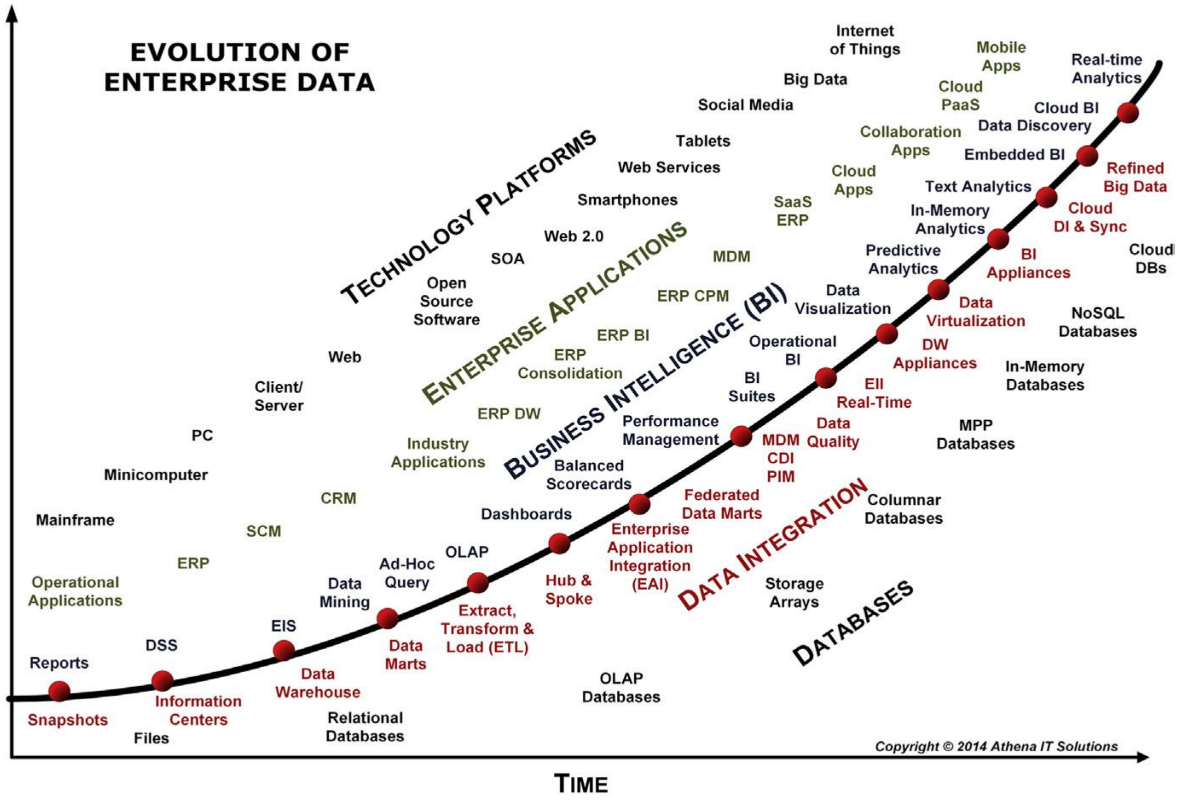

Figure 2.1 The evolution of enterprise data
(Source: Sherman, 2014, p.77)

Within an analysis of BIS development conducted by Olszak (2016), it is argued that three broad categories or stages can be seen within the evolution of BISs. Firstly, there was the initial stage of BI known as BI 1.0, which occurred between the 1970s and 1980s and has a close relationship to the management IS, the executive IS and the decision support system (Watson and Wixom, 2007; Thamir and Poulis, 2015). The applications and technologies commonly used within these ISs had a foundation in basic methods of statistics and simple techniques of data mining (Olszak, 2016). BI 1.0 had the capability of processing simple tasks for tactical and operational management, with a focus on delivering to the consumer, where notable market leaders included IBM and SAS (Gratton, 2012; Liu, 2016). The second BI era from 1990 to 2005 was associated with further advances in data warehouse development, along with new techniques of data mining and online analytical processing, most notably with internet technology including search engines (e.g. Yahoo and Google) (Olszak, 2016). Those technologies enabled organisations to present their businesses online and to have direct interaction with their customers, with text and web analytics being commonly employed in the processing and analysing of unstructured kinds of online content (Olszak, 2016). The many applications of Web 2.0 have, in addition, led to the creation of an abundance of content that is user-generated, hailing from various forms of social media such as blogs, online groups, forums, sites for social networking and social media, social games and even virtual worlds (Gratton, 2012). BI 3.0 represents a new era within the BI evolution, wherein there has been increased reliance on the internet, as well as mobile devices such as mobile phones, tablets and other kinds of internet-enabled, sensor-based devices that are equipped with radio tags, barcodes and radio-frequency identification (RFID) (Olszak, 2016).

Nowadays, it would seem to be possible to create innovative kinds of application and intelligent forms of business networks to cater for all needs (Chen et al., 2012; Olszak, 2016; Xin and Choudhary, 2019). Scott (2013) notes five core attributes that are supportive of the philosophy of BI 3.0: real-time, proactive, operational (availability for line workers), integration with business processes, and extensible for reaching beyond organisational boundaries so that information delivery can be improved along with the functionality of decision support for all. There is also an indication that there are no reasons for deprecating BI 3.0 functions retained from BI 2.0, such as data mining and online analytical processing, since these still offer useful and necessary functions (Olszak, 2016). The philosophy of BI 3.0 is to increase the added value for the architecture of BI tools through the anchoring of styles of collaboration for the search and analysis of information through the provision of self-service and intuitive interfaces that deliver highly relevant and timely insights to all those with the required authorisation (Nemec, 2012). Finally, it can be noted that a new BI trend has been emerging, known as ‘BI services on demand’ or ‘cloud BI’ (Olszak, 2016). A model is presented by cloud BI that offers access on demand to hardware and software resources with the minimum of effort for managers (Tamer et al, 2013; Olszak, 2016). It has been observed that cloud BI is a concept for the delivery of BI capabilities that is revolutionary in that it is a service that employs cloud-based architecture that is more cost-effective, and yet flexible and faster in its deployment (Gurjar and Rathore, 2013). The solution of cloud BI is of particular interest to organisations desiring improved agility, whilst simultaneously reducing the costs of IT and managing to exploit cloud computing benefits (Ouf and Nasr, 2011; Olszak, 2016).

2.3.3 The value of business intelligence

BI relates to all industries and all of their functions, touching everyone within a company and extending to include suppliers and customers (Howson, 2007; Davenport, 2012). Business value can only be provided by BI when it is utilised effectively. A clear relationship exists between effective BI use and the performance of a company (Howson, 2007). However, company performance is not affected by having improved access to data, but rather a difference arises through the manner in which data are employed by companies (Howson, 2007; Cosic et al., 2015). Nowadays, BI has undergone more extensive development over a much longer period in comparison to other forms of IS. In the years to come, there is highly likely to be further exponential growth in the market size for BI software as more businesses begin to discover the vast numbers of applications available for every operational facet, which offer great value and benefit for the organisation (Sugumaran et al., 2017).

In a 2018 report, over 46% of small business were found to use the virtual networking features of BI tools as a core aspect of their business strategies (Grand View Research, 2019). However, BI is only relied upon by 37%of manufacturers in the Asia-Pacific region (International Data Corporation, 2018). There is predicted to be an expansion of the global market for BI from US$ 15.64 billion in 2016 to US$ 29.48 billion in 2022, based on a compound annual growth rate of 11% (Statistics MRC, 2017). As a leading firm for business analysis, Gartner (2019) indicates that revenue for BI reached US$ 21.6 billion in 2018, representing a 11.7% increase from 2017. Gartner (2019) forecast that the market will grow by the close of 2020 to US$ 22.8 billion. The benefits of BIS implementation have been well defined and include enhancements in relation to decision-making (Arnott, 2008; Yeoh and Koronios, 2010; Işık et al., 2013; Audzeyeva and Hudson, 2016; Yeoh and Popovič, 2016; García and Pinzón, 2017).

The development of BISs represents a substantial organisational investment and, as such, it is important that it achieves a positive return on investment (Hatta et al., 2017). Furthermore, it will be significant to have measurements for qualitative values in order to justify investments that are made in IS (Yogev et al., 2012). Rouhani et al. (2012) stress that the transformation of the potential of BI into real value for business has criticality for companies. The need to create infrastructure and explicit strategies for BI is emphasised by Rouhani et al. (2012) so that information value can also be maximised. The business value and suitable handling of BI have great importance; however, for both practitioners and users, it is key to ensure best practice for both opportunities and solutions (Howson, 2007). Chamoni and Gluchowski (2004) suggest that there is significance in organisations striving for mature kinds of BISs so that true benefits can be captured from investments in BI, while Rezaie et al. (2017) argue that BISs are introduced to improve the quality and timeliness of inputs to the process of decision-making. Woodside (2011) emphasises that a BIS ought to have a fundamental purpose of providing the capacity for organisations in the monitoring of business operations and performance, and providing assistance to management in the development of business strategy and actions. Further, a key benefit for any system of BI is the provision of the right information at the appropriate time, so that decision-makers are able to make BI-informed decisions that enhance organisational performance.

BIS implementation is widely considered to be an important IT initiative for the improvement of organisational performance (Mesaros et al., 2016), even though the business world is complex, broad in scope and turbulent in nature, which makes the measurement and management of corporate performance particularly challenging (Salmasi et al., 2016). Complemented by the introduction of new approaches to management and relevant changes to the organisation, there is an expectation that BIS implementation and its effective use will add value to the organisation (Dawson and Van Belle, 2013). With decision-making increasingly being based on facts, recognition of BI's competitive value, the increasing requirement for compliance with changing regulations, and constraints on budgets, along with pressure for return on investment in IT, all manner and size of organisation are being compelled to ensure the successful adoption and effective use of BIS (Anjariny and Zeki, 2013; García and Pinzón, 2017). The result is that BIS, in the longer term, may result in optimised processes of decision-making and make a contribution to performance improvements (Grublješič and Jaklič, 2015). Through its assistance in identifying opportunities and problems, as well as aligning operations to corporate strategy within the process of decision-making, a system of BI contributes both to an organisation's sustainable development for organisations and competitiveness (Hatta et al., 2017). As BISs support intelligent forms of data exploration, data aggregation and integration, and multidimensional data analysis that originates from diverse sets of informational resources, the delivered intelligence can be rich in both reach and scope (Olszak and Ziemba, 2012). Furthermore, BISs can contribute to improvements in the performance of organisations through the timely delivery of management information that is actionable, alongside organisation information synchronisation and processes for decision-making (Acheampong and Moyaid, 2016).

The introduction of BISs within organisations is also often driven by requirements for improvements to business-related information necessary to support decision-making (Yeoh and Popovič, 2016). Moreover, and as Grublješič and Jaklič (2015) explain, there is the transformation of data into a corporate resource with a shift in focus from knowledge quantity to knowledge quality. Consequently, BISs are designed for the delivery of more than just raw data. Indeed, BISs add value through the transformation of raw data into information that may be exploited more readily for enhancing both operational and strategic decision-making. However, Popovic et al. (2012) report on the challenges of measuring the benefits that BISs deliver, since the returns happen in the longer term and can often be indirect. The extent that those benefits can be realised depends, to a large extent, on the manner and extent to which a system is used. A study undertaken by Audzeyeva and Hudson (2016) reveals that decision-makers interviewed within UK banks, many of whom had received formal training with respect to using sophisticated forms of technology to support decision-making, often utilised the technology infrequently when they were making decisions. These decision-makers claimed that sensitivity with respect to the political context and intuition were the factors that took precedence over rationality within the process of decision-making.

Generally, BISs are perceived as tools that support decision-making, and therefore are in operation at the senior and middle levels of management. Nevertheless, they have widespread impacts since they allow access to data for people at numerous organisational levels and enable data interaction and analysis so that the business can be managed and operated more efficiently (Liebowitz, 2006). BISs are often viewed as a form of innovation that can lever wealth from transactional stores of data within a system of an enterprise, and can support the transformation anticipated to broader systems of management control (Howson, 2007, Salmasi et al., 2016). Previously, BISs were seen as tools exclusively utilised for supporting strategic decision-making (Yeoh and Koronios, 2010). Through the deployment of these kinds of BI technology and systems for supporting broader activities of business, organisations now use them for improving operational processes, as well as customer service and the management of the supply chain (Williams and Williams, 2007; Laudon and Laudon, 2017). Integration of BISs with the processes of business enables management to access information that is timely and relevant, and thus to make better decisions with regard to business operations (Woodside, 2011). As well as contributing to improvements in corporate performance and decision-making, BISs also help generate benefits in operational terms throughout the value chain (Howson, 2007).

In summary, it can be stated that the achievement of value from any kind of IS innovation is realised through its direct impact on the processes of the business, and in that regard, BISs are no different (Negash, 2004; Walsham and Sahay, 2006; Olbrich et al., 2012; Wixom and Watson, 2012; Wallace, 2015). Business information and capabilities in analysis can be delivered by BI techniques and tools in order to assist companies in the optimisation of the operational performance to support the designs of their business (Williams and Williams, 2007). When such software is implemented, some of the most significant benefits of BI include improved asset utilisation, reduced cycle times, improved service, improved quality and reduced costs, all of which can contribute to increased profits (Williams and Williams, 2007). It is suggested by Stair and Reynolds (2018) that numerous benefits may be achieved through the use of BI, including the detection of fraud, improved forecasting, increased sales, the optimisation of operations, and a reduction in costs. Puklavec et al. (2017) concur with those points while arguing that the benefits hailing from a system of BI in respect to improved decision-making may only be gleaned if the decision-makers actually use the BIS. The suggestion can therefore be made that although organisations can invest substantial resources in BIS development, the potential benefits may not be realised unless the system is adopted and utilised by the significant decision-makers.

The next section presents a discussion surrounding the primary and most critical benefit that companies aim to achieve through the implementation of BI, namely enhanced decision-making quality. Therefore, decision quality is defined and consideration is given to how decision quality is to be measured within this study.

2.4 Decision quality

Nowadays, decisions of poor quality within business are endemic (Spetzler et al., 2016; Bolam et al., 2019). Nutt (2011) points out that approximately half of all decisions that are made within organisations fail; therefore, failure occurs far more often than previously thought. Unfortunately, since Nutt's study there has not been a significant improvement as poor decision-making continues to fill the headlines and impact on organisations across the globe (Spetzler et al., 2016). As a result, tremendous economic value is being lost to the global economy in general, and for shareholders and companies in particular. Furthermore, poor decisions do not only hail from the world of business. People working within all types of organisations such as not-for-profit agencies and governmental departments are making poor choices that lead to expensive consequences. Individuals, of course, make personal decisions that can have costly consequences for their own lives and prosperity (Spetzler et al., 2016; Marino and Eastman, 2017; Bolam et al., 2019). As a term, a 'decision' refers to a choice made between at least two alternatives involving irrevocable resource allocation (Howard and Abbas, 2016). Decision-making is, however, a cognitive process that leads to the selection of a particular course of action from amongst alternatives, and which results in decision-related outcomes (Dean and Sharfman, 1993). Decision-makers need to address problems that are interrelated and complex. As the problems faced are both dynamic and routine in nature, there is a need to make several decisions rather than just one; these will have interdependency, while there are periodic changes to the environment in which those decisions are made (Chewning and Harrell, 1990; Keeney, 2004). Therefore, decision-makers need to pass through a series of stages prior to arriving at a decision: firstly, there are the inputs, which are the factors that decision-makers rely upon within the process of decision-making; secondly, there is the processing of functions if inputted; and thirdly, there are the outcomes of decision-making that are the process outputs (Dean and Sharfman, 1993; Vroom, 2000; Heyler et al., 2016; Bernardino, 2017). Decision-making is a powerful skill for shaping futures. Indeed, being able to make good decisions is key to success in life (Spetzler et al., 2016); however, the difficulty in establishing measures that directly account for decision quality is largely as a result of the complexity within the processes of decision-making (Kariv and Silverman 2013; Visinescu et al., 2017).

The quality of a decision is a function of efficiency and effectiveness within the decision-making process (Clark et al., 2007). While decision quality may aid us in creating better habits that make decisions more efficient and effective, its most pertinent use is within those decisions that mould our lives and success in business, from the selection of a career to decisions over the growth of a multinational company. Such decisions require focus on quality and careful deliberation (Spetzler et al., 2016). To make judgements on decision quality prior to action, decision-makers need to have an understanding of the integral aspects. Spetzler et al. (2016) suggests that decisions can be categorised into six distinct elements that have to be addressed when considering quality, and therefore there are six requirements in relation to decision quality: i) there is a need for a frame that is appropriately suited for the circumstances in question; ii) alternative possible courses for action must be considered; iii) reliable and relevant information is required; iv) clear values need to be established along with preferences (trade-offs); v) there must be sound reasoning based on approaching the information available and integrating it alongside the values and alternatives so that the delivery is most suited to that wanted by the decision-maker(s); and vi) committed action is required that involves the appropriate people within the efforts to form the decision (Spetzler et al., 2016).

Often, decision-making quality is viewed in respect to the outcomes emerging from a specific decision; however, the literature suggests that there cannot be measurement of the final outcomes of decisions (in terms of whether they are of low or high quality) since it is often the case that good decisions can result in outcomes that are unfavourable if the implementation has been poor or if unforeseen factors came into play following the making of the decision (Lipshitz and Strauss, 1997; Brown, 2012; Keisler and Noonan, 2012). As such, whilst any particular decision could have been considered as having good quality when it was made, ultimately there may be other factors that have an impact on the final outcome quality. Given that the association to outcomes is an ambiguous one, researchers have suggested that decision quality ought to be defined with regard to other terminology (Edwards et al., 2009). There appears to be a paucity of research that provides concepts for the measurement of decision quality within organisational settings through employing measures without tangible association to the outcomes of the particular decisions that are made (Lipshitz and Strauss, 1997). However, the measurement of the perceived quality of the decision can also be problematic, with Cox and Davison (2005) noting that in general there is involvement of subjective measurement through the use of a self-reporting indicator set or an expert panel. Priem et al. (1995), for instance, employed two independent professors of strategic management for the judgement of decisions using a 5-point Likert scale that extended from high to low quality. Another approach was taken in a study by Cardella (2012) through using measurement achieved by means of experimental design, wherein a game was played by the participants in which they learned through observation, and which resulted in improvement in decision quality that was measurable in terms of a player's success within the game.

It is reasonable to make the assumption that managers of seniority would hold perceptions with regard to the quality of the strategic decisions made. Moreover, given that decision-making can be highly complex, it is reasonable to assume that perceptions related to quality should be founded on multiple elements. Kopeikina (2005) suggest that the decision quality may be assessed in terms of three dimensions: i) the decision-making process quality, ii) the content of the decision-making, and iii) the internal alignment that the decision has with the vision of the organisation. In relation to the perceptions of senior managers, the focus of Michie, Dooley and Fryxell (2006) was placed on i) the information quality within the decision-making, ii) the alignment that the decision has with the current strategy, iii) the financial responsibilities with respect to the decision, and iv) the overall contribution of the decision to the effectiveness of the organisation. The conclusion of their study is that improved decision quality manifested within diverse teams that had a high level of goal consensus or alignment with the objectives and goals of the organisation (Michie et al., 2006). Raghunathan (1999) maintains that improved quality of information, when combined with improved quality of the decision-maker, leads to the making of higher quality decisions. Furthermore, he specifically highlights that the provision of support tools (e.g. BIS) for quality decisions is important for the enhancement of the process of decision-making, which closely aligns with Stair and Reynolds's (2018) suggestion with regard to the significance of the impact of information quality (in respect to the information employed in reaching a decision) on the resultant quality of that decision. An organisation with an emphasis on using sophisticated forms of data analysis and advanced types of IS without prior consideration of the quality of the information used is destined to make a high number of flawed decisions (Stair and Reynolds, 2018).

Another decision quality measurement is the perceptions related to the likelihood of an intended outcome being achieved (Wood and Klass, 2008). Carmeli et al. (2012) also used this approach in a study that asked senior managers for their assessment of recent decisions that they had made based on i) the effect that the strategic decision had on the organisation, ii) the results of the strategic decision when compared with expectations (i.e. were the intended outcomes achieved?), and iii) the perception of overall success in relation to the strategic decision made. Other researchers have measured decision-making in relation to the outcomes of decisions (Giddens, 1984; DeSanctis and Poole, 1994). Vessey (1991) explored decision-making in respect to the performance in problem-solving, while Langer (1975) investigated decision-making in relation to the expectancy of success. Other perspectives include that of Galbraith (1974), who studied the performance in processing information, and Kahnernan and Tversky's (1979) focus on the risk preferences of decision-makers. Cohen et al. (1972) considered decision-making with regard for the manner in which decisions are structured and made. Others have defined decision quality in respect to employing experts for the identification of what would constitute the optimum decision, as well as what would constitute the most suitable criteria for achieving a high degree of decision quality (Ross, 1974; Jacoby, 1977). Within the context of IS, an approach that is most noticeable is the measurement of the outcomes of decision quality through the perceived satisfaction of decision-makers, with the outcome being utilised as a decision quality surrogate (Galbraith, 1974; Speier et al., 1999; Kaltoft et al., 2014; Visinescu et al., 2017). This study adopts that approach and the conceptualisation of decision quality in terms of the perceptions of the decision-makers and their satisfaction levels in respect to the outcome that results following the process of decision-making. Within Chapter 3, (section 3.2) and Chapter 4 (section 4.6.1), further descriptions can be found of the approach taken in terms of the measurement of decision quality.

2.5 Gaps in the literature

This review regarding the implementation of BI has revealed several gaps within the literature. The majority of studies (see Figure 2.2, Appendix 1) have been conducted within developed country contexts (Wixom and Watson, 2001; Xu and Hwang, 2007; Arnott, 2008; Hwang and Xu, 2008; Yeoh and Koronios, 2010; Woodside, 2011; Işık et al., 2013; Audzeyeva and Hudson, 2016; Hung et al., 2016; Yeoh and Popovič, 2016; Puklavec et al., 2017), with little empirical research being undertaken within developing countries (Hasan et al., 2012; Anjariny and Zeki, 2013; García and Pinzón, 2017; Rezaie et al., 2017). As a result, there is a dearth of knowledge regarding the implementation of an environment of BI within developing and less developed nations. Furthermore, due to their lateness in the adoption of technology, there is limited research in relation to the MENA region (Stafford et al., 2006), with the majority of IS adoption within MENA countries taking place within the 1990s (Ali, 2004), thus exemplifying how social and cultural factors seem to exert a significant influence in shaping perceptions towards the acceptance and adoption of IT (Stafford et al., 2006). The implication is that BI within Jordan could differ from that seen in other developed countries. When exploring the critical success factors (CSFs) in relation to the implementation of enterprise resource planning within Jordan, Abu-Shanab et al. (2015) found that enterprise resource planning/IS implementation projects have tended to be relatively unsuccessful. As a country in development, Jordan faces a range of challenges when IS, technologies and management techniques and processes that have already been established and formulated within other developed countries are being implemented (Al-Shboul et al., 2014). Furthermore, relatively few studies have been undertaken in relation to BISs within Jordan (Ait-yassine, 2012; Al-Zubi et al., 2014; Malkawi, 2018) with virtually no studies having been undertaken into BI implementation within the Jordanian mining sector. As such, with the aim of providing a more detailed perspective on which factors are applicable within the environment of the mining sector in Jordan, there is a requirement for further research that studies those implementation factors that have a bearing upon BI success in this national context.

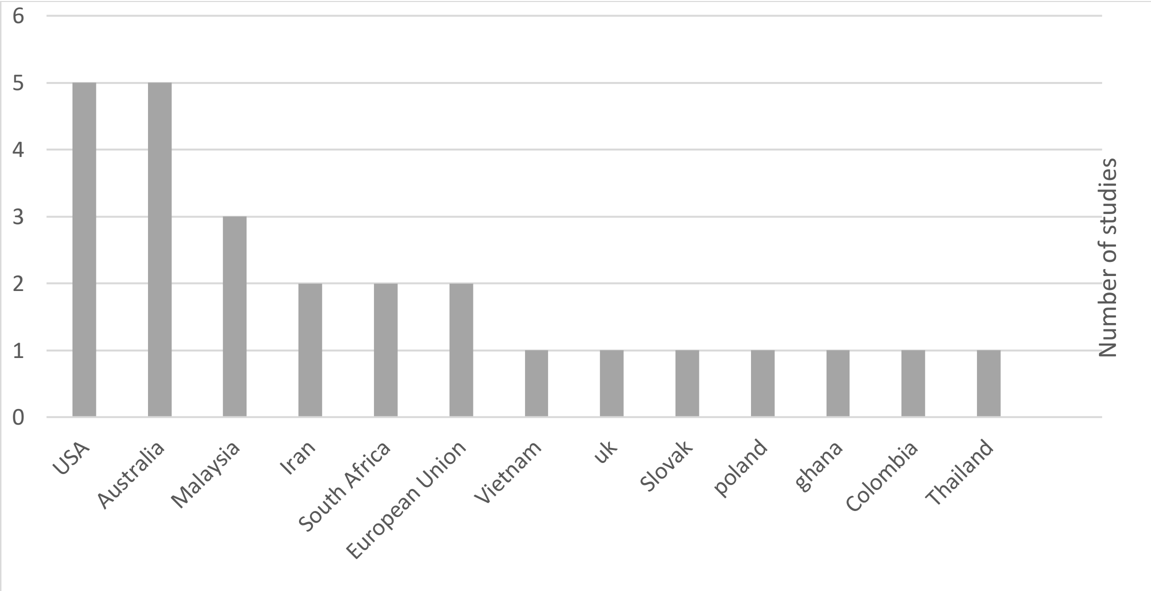

Figure 2.2 Number of studies conducted on BI implementation in a selection of developed and developing nations.
(Source: the author)

The literature related to the implementation of BI has also shown there to be a variety of factors that could impact on BI success (Arnott, 2008; Hwang and Xu, 2008; Hasan et al., 2012; Olszak and Ziemba, 2012; Dawson and Van Belle, 2013; Işık et al., 2013; Puklavec et al., 2014; Grublješič and Jaklič, 2015; Nasab et al., 2015; Hung et al., 2016; Mesaros et al., 2016; Pham et al., 2016; Yeoh and Popovič, 2016; García and Pinzón, 2017; Hatta et al., 2017; Lautenbach et al., 2017; Owusu et al., 2017). Whilst several models of implementation have discussed the success of BI as being a critical issue within the literature, there is room for improvement within this field through the assessment of those models, as discussed further in Chapter 3 (section 3.3) through the use of the semantic approach to reviewing literature. The conclusions were primarily drawn from studies that had been previously undertaken with regard for BI implementation and success, and the identification of the implementation factors that have a bearing on BI success.

There is also a limited amount of research that has discussed the evaluation of the success of BI. Wixom and Watson (2001), for example, identify data quality, perceived net benefits and system quality as being success factors in the measurement of the impact of implementation factors. Their study also offers a comprehensive model of research with regard to BI implementation, although it is one of only a small number of such studies that have solely focused on the factors of BI implementation and success (Hwang and Xu, 2008; Yeoh and Koronios, 2010; Yeoh and Popovič, 2016). Furthermore, those studies lack the identification of relationships between the variables of BI success and the impact that they have on decision quality. Therefore, a clear gap in the literature has been identified, which this study aims to address by placing its focus on the development of a conceptual model for the identification of the implementation factors that have an effect on BIS success at three different levels—semantic, technical and effectiveness—as shown in Chapter 3 (section 3.2).

2.6 **Chapter summary**

This chapter has presented a review of the literature concerned with BI and IS, and the key issues in relation to their evolution, definitions and implementation, as well as their success or failure. Those issues have been explained through the identification of their primary characteristics and the various perspectives of them, as well as the interactions required during the implementation of an IS. The multiple definitions, interdisciplinary nature and variety of meanings reflect the complexity within BI and IS. The literature reviewed for inclusion within this chapter has been helpful in developing a greater understanding of the impediments and challenges for achieving successful implementation of BI, as well as clarifying the various opportunities provided for improving decision quality for the users of BI. Moreover, this chapter has highlighted gaps within the existing literature related to the topic of interest and forwarded an overview of commonly used theories that are employed within research exploring the success of IS. Based on the gaps identified in the literature and the theories of IS success, Chapter 3 forwards a conceptual study framework that will be adopted in order for these gaps to be filled.

Chapter Three:
Conceptual
Framework

3.1 Introduction

This thesis investigates the effect of the BI implementation factors on the project and the potential for successful outcomes within the mining sector in Jordan. Therefore, prior to focusing on the methodology of the study, an understanding is necessary of the conceptual framework that serves to explain the relationships between the implementation factors and the success of BI, so that BI project success can be maximised. This chapter provides analyses of numerous success models for IS and BI that have been developed, validated and widely used, along with theories focusing on factors that have an effect on the implementation and success of the system. The background in theory serves as a foundation for the description and development of the model or framework for the study, as well as the hypotheses put forward. There are six sections to the chapter. Section 3.2 describes common frameworks for theory within the field of BI and IS success, along with a selection of the dependent variables (BI success) for the research model. Moreover, there is a discussion of the key theoretical bases for the study of BI and IS. Within section 3.3, the selection of the independent variables that form the implementation factors applied within this research project is presented, as well as an explanation of the rationale behind the selection made. Subsequently, section 3.4 presents and discusses the study's conceptual framework. Then, section 3.5 features the hypotheses development related to the impact of twelve implementation factors (i.e. business plan and vision, management support, champions, resources, project management, team skills, change management, data source systems, IT infrastructure, attitudes toward technology, trust and user participation) on the success of BI (i.e. information quality, system quality and decision quality). Finally, the chapter is concluded in section 3.6.

3.2 Dependent variables: business intelligence success

As Sekaran and Bougie (2016) note, the dependent variable is the primary variable that any research is focused upon. The dependent variable is also known as the endogenous variable or the criterion variable (Hair et al., 2018). Within this research, the primary dependent variable is BI success. Effective system success occurs if a system fulfils the objectives, whilst efficient implementation manifests if there is completion of the system implementation within the allocated time, budget and effort. Implementation may be efficient though not effective, and vice versa (Garrity and Sanders, 1998). If that situation transpires, other measures of success must be arranged. Models and theories have been developed by numerous researchers, which have been tested in order to assess the IS success within diverse domains and scenarios (Anjariny and Zeki, 2013; Işık et al., 2013). The models that have been tested and used most commonly within the BI success domain include, amongst other models and theories, the IS success model proposed by DeLone and McLean (1992), the data warehouse success model proposed by Wixom and Watson (2001), the data warehouse success model proposed by Hwang and Xu (2008), and the model for implanting BIS developed by Yeoh and Koronios (2010). Within the sections that follow, those models and their variables are explained, along with a discussion on their utilisation.

- ***DeLone and McLean's information system success model***

The key theoretical framework employed within this research is the model for IS success that DeLone and McLean (1992) put forward, referred to here as the IS success model (see Figure 3.1), which has become a leading choice for dependent variables by researchers of IS (Hwang and Xu, 2008). Following a review of 100 papers that contained empirical measures of IS success and were published within seven top publications in the period from 1981 to 1987, there was categorisations of the empirical measures for IS success into six different dimensions. Based on DeLone and McLean's taxonomy, system quality lies at the technical level and information quality sits at the semantic level, while user satisfaction, use and impact can be found at the effectiveness level. The hierarchy for those levels serves as a foundation for the causal and temporal interdependencies amongst those six dimensions (see Figure 3.1). The model makes a significant contribution to the IS success measurement literature since it offers a scheme for the classification of the plethora of measures of IS success, whilst also suggesting the causal and temporal interdependencies amongst those categorisations (McGill et al., 2003).

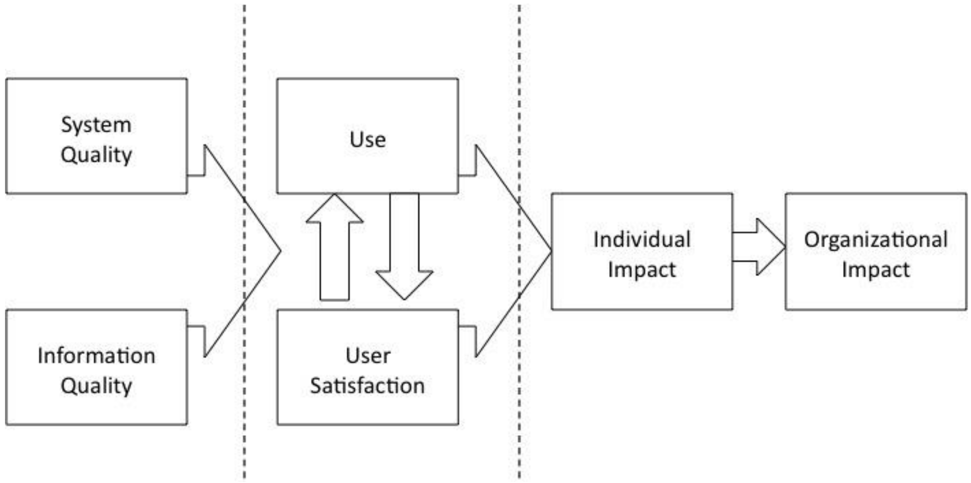

Figure 3.1 DeLone and McLean's IS success model (1992)
(Source: DeLone and McLean, 1992, p.87)

Sabherwal et al. (2006) note that when proposing their model of IS success, DeLone and McLean (1992) had not empirically tested it; however, since then numerous studies have sought to test and validate the model, as well as to modify and develop it. The first to test the process/causal nature of the model were Seddon and Kiew (1996), followed by Seddon (1997) who extended and re-specified the IS success model and put forward an alternative model. Both Sabherwal et al. (2006) and Rai et al. (2002) further built upon DeLone and McLean's (1992) model. Seddon (1997) argues that DeLone and McLean attempted to achieve too much through combining both causal and process explanations for success in IS within their model, and that this led to the model being misspecified and confusing. Seddon's (1997) study has importance since it adopts a theoretical approach for the modification of the IS success model since a distinction is made between the expected and actual impact, as well as the incorporation of the further perceived usefulness construct (Sabherwal et al., 2006). Seddon (1997) argues that successful systems will be beneficial in terms of helping users to carry out better and/or a greater volume of work within the same period of time, or to achieve work of equivalent quality within a lower time period. DeLone and McLean's model was augmented by Pitt et al. (1995) with the inclusion of service quality as an IS success measure, with the argument that the IS success model requires expansion in order to reflect the service role of the IS department. Furthermore, since the categorisation theory of

DeLone and McLean has a basis in communication, the IS department is not solely a provider of products, but is also a provider of services. Petter et al. (2008) note that many researchers have made the suggestion that service quality is a significant factor for addition to DeLone and McLean's model of IS success since it has salience for the success of IS. There is also a danger that IS effectiveness is incorrectly measured if a service quality assessment is not included by the researchers. Service quality is defined by Petter et al. (2008, p. 239) as "the quality of the support that systems users receive from the IS department and IT support personnel". Furthermore, rather than individual applications of IT, it is a measure of IT department service quality through the measurement and comparison of the expectations of users and the perceptions that they have of the department (Petter et al., 2008). Within the IS literature, this argument has been supported; for instance, Watson et al. (1998) reported that after general service quality, the second most important user satisfaction component is the match that exists between the actual service of the IS and the expectations of users. Meanwhile, Bhattacherjee (2001) found that the overall satisfaction was strongly affected by the fulfilment of the user's expectations, while Pitt et al. (1995) proposed that there can be an assessment of service quality through the measurement of the expectations and perceptions of customers in relation to the level of performance for a variety of attributes of service. Then, there should be calculation and averaging across attributes of the difference between perceptions related to the actual performance and expectations. A number of years later, DeLone and McLean (2003) conducted a review and evaluation of this argument prior to the updating of their model of IS success, based on a review of over 100 articles within the conceptual, empirical literature on the success of IS that had been published in those intervening years. Consequently, the IS success model was modified with net benefits replacing organisational and individual impacts, and the introduction of the 'intention to use' within the updated version of the model of IS success (see Figure 3.2) (DeLone and McLean, 2003). For Adamala and Cidrin (2011), a key disadvantage of this framework is a failure for any specific measurement approaches to be proposed. Moreover, no explanations of the variables employed are provided by the model, which is left to the users to determine.

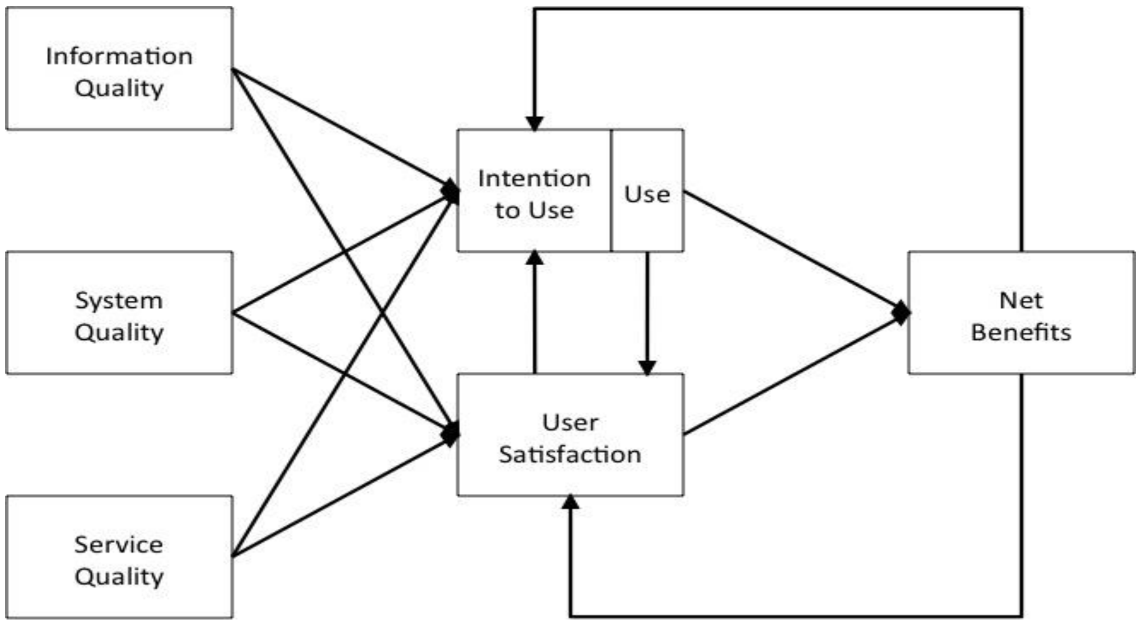

Figure 3.2 DeLone and McLean IS success model (2003)
(Source: DeLone and McLean, 2003, p.24)

The DeLone and McLean (1992) model of IS success has been cited in at least 144 studies (DeLone and McLean, 2002). A multi-dimensional criterion set for the success of IS was offered by that original model; however, empirical model validation was nor provided, and the emphasis was placed on the need for additional research so that the validity of the model could be authenticated. Since this model was published, several studies have conducted empirical investigation of the interrelationships proposed amongst the IS success measures. This model has been adopted by several researchers in order to study various types of ISs such as e-commerce (Molla and Licker, 2001; DeLone and McLean, 2003), decision support systems (McGill et al., 2003), accounting ISs (Seddon and Kiew, 1996), enterprise systems (Gable et al., 2003), data warehousing (Wixom and Watson, 2001; Shin, 2003) and integrated student ISs (Rai, 2006). These studies have, on the whole, provided robust support for the dimensions of success and helped in confirming the temporal and causal model structure (Garrity and Sanders, 1998). If judged by the frequency of citation within published articles in the leading IS-related journals, there is confirmation that the IS success model is indeed a framework that is useful for understanding the success of IS (Petter et al., 2008). This is in part due to it being adaptable to specific contexts of research, as noted by DeLone and McLean (1992, 2003), with the suggestion that appropriate measures are selected from the model to suit researchers' particular needs.

- ***The Wixom and Watson data warehouse success model***

The Wixom and Watson (2001) model offers a deeper analysis for this study in terms of BI success. Data warehousing serves as the source in technological terms for BI, and thus it has been established as a significant component for the success of BI. The research model was developed by Wixom and Watson (2001) to explain the relationships amongst factors affecting the success of the data warehouse (see Figure 3.3), and helps in identifying the various analysis levels required and the impacts associated at each of the levels. The increasing model richness suggests that a more differentiated and subtle interaction exists between the elements, and a reduction in dependence on a few CSFs. Numerous theoretical approaches are integrated in the model, although essentially it relies upon DeLone and McLean's (1992) IS success model. Two dimensions defined in the 1992 version of the IS success model were excluded by Wixom and Watson (2001) (i.e. user satisfaction and benefits at the organisational level that measure the success of the system), due to user satisfaction being considered less suitable since the perception of the end user is typically based on one application, whilst the authors argued that multiple applications are supported by a data warehouse rather than it being, itself, merely an application. Additionally, there was exclusion of the organisational impact, since the argument was made that the organisation was affected by external factors beyond control and that the study of those factors could not be repeated. Wixom and Watson's model includes implementation factors (i.e. champion, manager support, user participation, resources, source systems, development technology and team skills) that are assumed to have an impact on implementation success in three phases: the organisational, the project and the technical stages. Consequently, three implementation success stages have a bearing on the success of a system as measured through system quality, perceived net benefits and data quality. Within this study of data warehousing, an emailed questionnaire related to the implementation factors and respective implementations' success for data warehouses was completed by suppliers and managers from 111 organisations. Significant relationships between the perceived net benefits, variables of data quality and system quality were identified from their research results. Nevertheless, Wixom and Watson's (2001) research model is limited in that there is a lack of strategic factor identification, such as noting the alignment of the organisation and the defined enterprise approach and business objectives, which would affect a data warehouse project's success (Hawking and Sellitto, 2010).

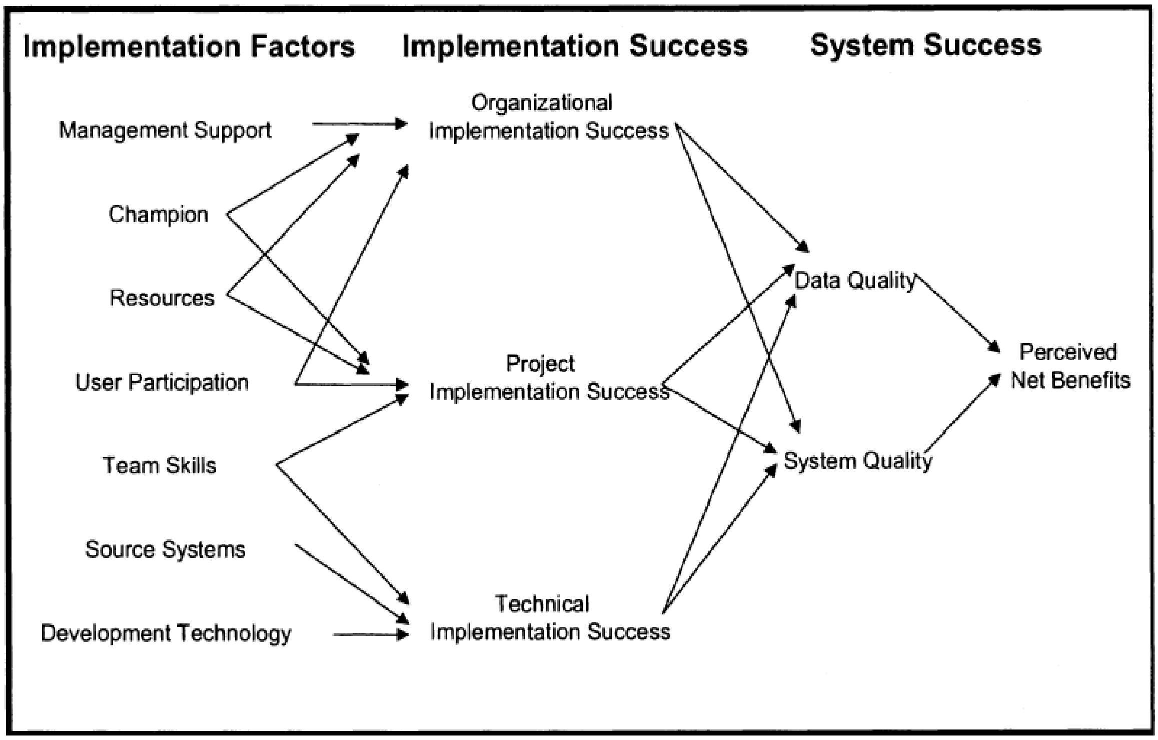

Figure 3.3 The Wixom and Watson data warehouse success model
(Source: Wixom and Watson, 2001, p.20)

- ***The Hwang and Xu data warehouse success model***

The 2008 model developed by Hwang and Xu is, once again, extremely dependent upon the IS success model of DeLone and McLean (1992, 2003). However, Hwang and Xu (2008) sought to expand the previous model with the coverage of more implementation factors instead of placing an exclusive focus on technical factors. Three groups form the primary factors of success: economic factors, technical factors and operational factors (see Figure 3.4). System quality is influenced by the outcome of the economic and operational factors, whilst system quality is the primary contributor of information quality, in alignment with those contributions made by a variety of technical factors. Individual system benefits are strongly dependent on information quality, whilst there is achievement of benefits for the organisation if a system is successful in its satisfaction of the original requirements. Hwang and

Xu's model has two major drawbacks in that i) the model lacks any method for objectively measuring CSFs, and ii) it is difficult to determine whether non-technical or technical factors play a significant role in the model for data warehousing success (Adamala and Cidrin, 2011).

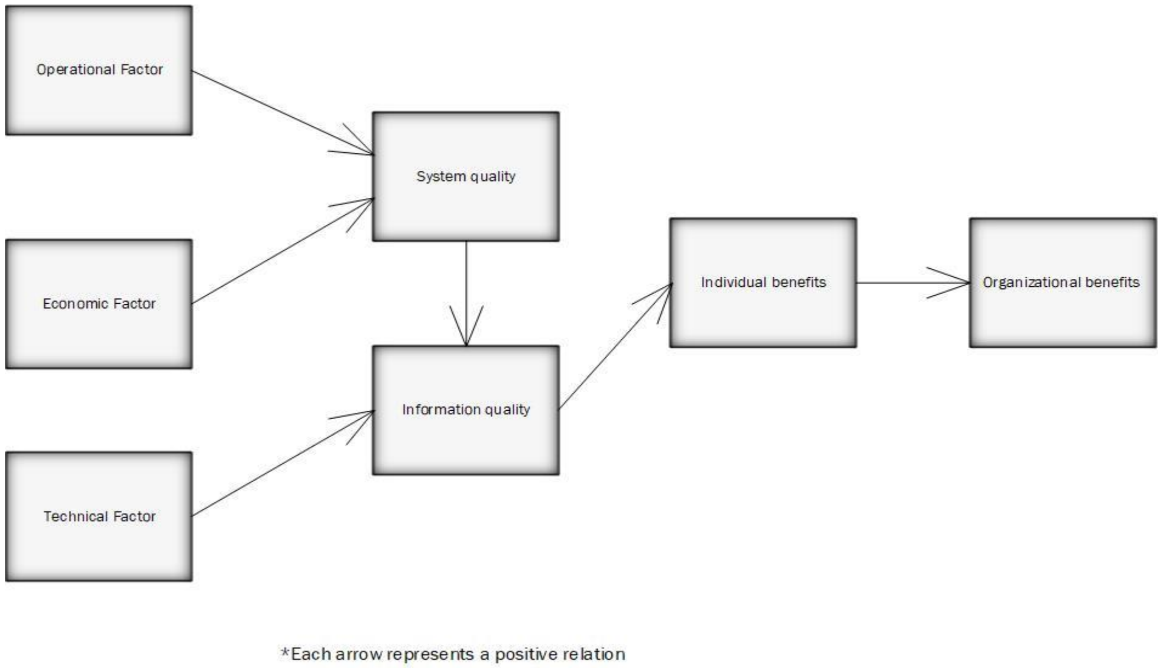

Figure 3.4 The Hwang and Xu model for data warehouse success
(Source: Hwang and Xu, 2008, p.54)

- ***Yeoh and Koronios's (2010) implanting business intelligence system model***

A framework for the implementation of BISs was proposed by Yeoh and Koronios (2010). A number of the variables of success identified within the work of DeLone and McLean (1992) are incorporated within Yeoh and Koronios's (2010) model, which identifies information quality, system quality, perceived net benefits and system use as the most suitable measures of success (see Figure 3.5). Their model also has the overall implementation factors placed within three groups, as identified in the work of Wixom and Watson (2001): i) organisation (vision and business factors, management, and championship factors), ii) process (team, project management, change management, and methodology factors), and iii) technology (data and infrastructure factors). It is proposed by the model that all CSFs impact on the overall business orientation. Subsequently, factors for infrastructure performance, process performance and business orientation are considered as resulting in the success of implementation, and therefore of perceived benefit to the business. The framework has considerably more suitability for systems of BI than the IS success model (DeLone and McLean, 2003), although the Yeoh and Koronios (2010) model has been criticised as there is no proposal of any particular methods of measurement (Adamala and Cidrin, 2011). Whilst the proposed framework of Yoh and Koronios (2010) has particular advantages and strengths, such as its flexibility when results are being reviewed, utilising the cycle of closed feedback and its CSFs' representations for the primary input for implementation success, it does also have some shortcomings and weaknesses. Adamala and Cidrin (2011) claim that no specific criteria for measurement are proposed by the framework for the various CSFs. This lack of clear criteria may be attributable to the definition in general of many of the CSFs, leading to difficulties in using measures that are consistent. The implementation of the framework, therefore, could be impractical and the use of it could be dependent upon subjective user opinion.

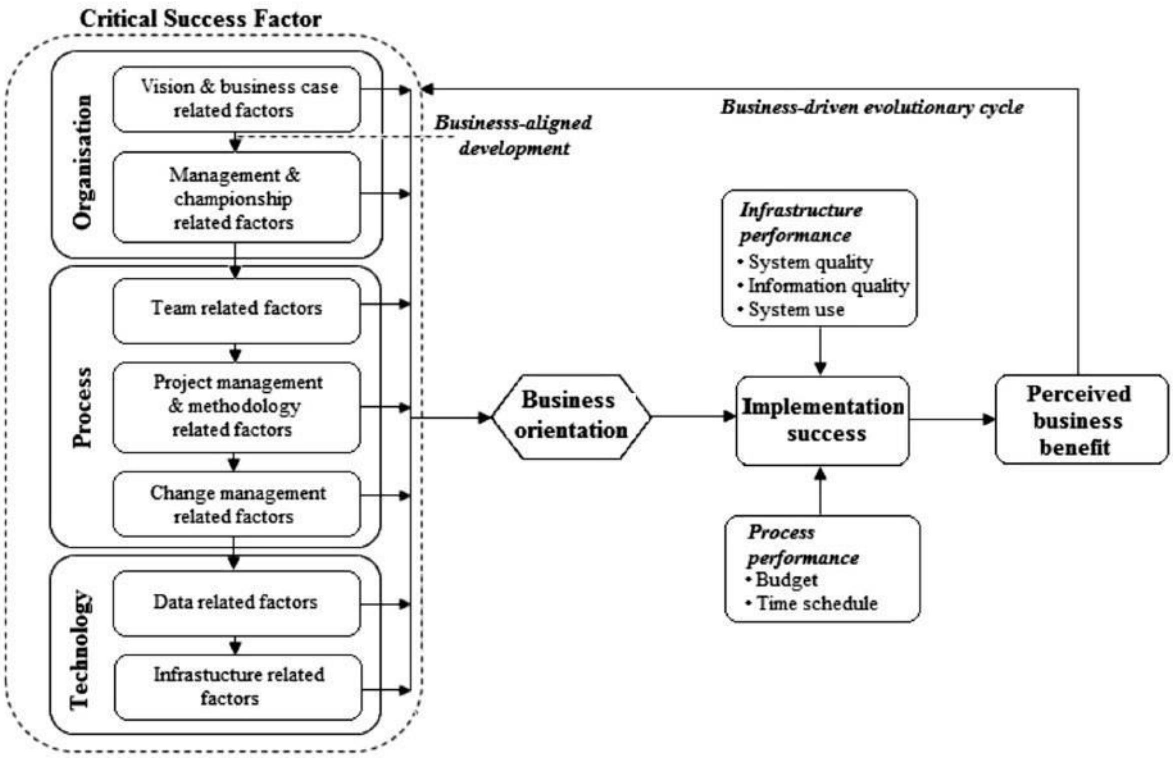

Figure 3.5 Yeoh and Koronios's model for the implementation of a BIS (Source: Yeoh and Koronios, 2010, p.25)

3.2.1 Selection of the variables for business intelligence success

Based on DeLone and McLean's (1992) model for IS success and following the review of the BI success model, three variables of success as proposed in DeLone and McLean's (1992) study are employed as the foundation for the variable of candidate success. The two system success variables are information quality at the semantic level, and system quality at the technical level. Success in one of those variables carries the implication that the system is successful. At the level of effectiveness, the third variable is decision quality, with this research aiming to investigate the impact of BI success upon decision-making quality within the Jordanian mining sector. Since the measurement of decision-making quality is often carried out through the perceived satisfaction of the decision-maker, the outcome often serves as a surrogate of decision quality (Galbraith, 1974; Vessey, 1991; Kaltoft et al., 2014; Visinescu, 2017). This research, as discussed in Chapter 2, selects decision quality, an aspect belonging to the level of influence (effectiveness) and represented within the model of DeLone and McLean by user satisfaction.

3.2.1.1 System quality

System quality is defined by Seddon (1997) as having concern for whether the system has bugs or not, whether the user interface has consistency and is easy to use, whether the program code is maintainable and of sufficient quality, and whether the documentation is of good quality. System quality is described by Chatterjee et al. (2009) as being the degree to which a system is able to effectively integrate data from various places with increased satisfaction and a higher level of use amongst users. Integration, resource utilisation and flexibility have all been utilised within previous research for the evaluation of system quality. Meanwhile, system quality is described by DeLone and McLean (1992) as a reflection of the performance characteristics that are more engineering-oriented for the system under investigation. The variable for success was conceived through aggregating measures from previous studies such as hardware performance, resource utilisation, response time, reliability, ease of use, completeness, flexibility and turnaround time (DeLone and McLean, 1992). In general terms, the quality of the system relates to how users view IS and what they feel about it (Song, 2010). In reference to the system characteristics and the manner in which information is processed and delivered, it is the extent to which the system is flexible and the volume of information it is capable of accessing (DeLone and McLean, 2003). Support for terminal hardware system that supports learning is provided by the work of Lucas and Nielsen (1980). System quality is described by Vandenbosch and Higgins (1995) in terms of its ease of use, reliability, and analytic capability. Nelson et al. (2005) consider system quality dimensions to be representative of the users' perceptions of their interactions with a system in the longer term. For Nelson et al. (2005), the characteristics of system quality are the same primarily, without much deviation for various users, and they may be assessed in a manner that is independent of the context, application or task. Through a literature review drawing on 20 studies, Nelson et al. (2005) suggest that five key dimensions for system quality are reliability, accessibility, response time, integration and flexibility. Accessibility is defined by Miller (1996) as the ability to obtain information when it is required. Furthermore, as Popovic et al. (2012) describes, even though there is broad recognition that technology primarily has an impact on the quality of information access with limited potential for impacting upon the quality of information content, there is a belief that by way of improvement to interactivity, knowledge workers are not merely delivered information but can also explore that information and obtain other information with greater relevance. Reliability has been defined as system dependability over time, which is measured by the period of time between failures or by the downtime or uptime (Nelson et al., 2005). Reliability has been considered to include characteristics related to the downtime of software and hardware, validity, technical quality and recoverability (Gorla et al., 2010; Filieri and McLeay, 2014). The response time is defined by Nelson et al. (2005) as the extent to which timely or quick responses in relation to requests for action or information are offered by a system, while Hackney et al. (2015) defines flexibility as the extent that the options and features in a system are amenable to accommodate change without program modification. Nelson et al. (2005) suggests that flexibility has greater importance in systems that execute functions of analysis that have a greater likelihood of changing over time. Meanwhile, they define integration as the extent to which systems facilitate the support of business decisions through combining information gleaned from a variety of sources (Nelson et al., 2005). Systems that help to integrate have to accommodate tasks that are interdependent, with agreement in respect to the meaning of the data being exchanged amongst ISs that are heterogeneous (Urbach et al., 2009) Within the literature on BI, system quality is thought of as a key measure of BIS success (Wixom and Watson, 2001). Within this research, BIS quality has been defined as the extent that a system is considered adaptable; reliable; easy to use, understand and maintain; and that the system functions are performed quickly (Barki et al., 2001).

3.2.1.2 Information quality

As Wang and Strong (1996) note, the term ‘information quality’ refers to whether information is valued for a particular use or purpose. It relates to the value of the produced output of a system as perceived by the users (DeLone and McLean, 2003). Information quality refers to the IS output characteristics such as the timeliness, completeness and accuracy (Petter et al., 2008). Often, information quality is considered as being a primary antecedent for user satisfaction (Urbach and Müller, 2010). Measures are subsumed that focus on information quality, which constitutes the desirable IS output characteristics produced by the system and its overall usefulness. Characteristics such as the clarity, goodness and relatedness of the delivered information are key IS features (Pearson et al., 2012). As outlined by DeLone and McLean (2003), information quality is related to issues such as output timeliness, relevance, completeness, reliability, and the accuracy and precision of the information that an IS generates. It is recognised within the literature that information quality is a construct that is multidimensional, with particular characteristics for indicating its presence within ISs (Lee et al., 2002). Often, those characteristics are grouped in categories or dimensions consisting of similar characteristics (Arazy and Kapak, 2011). Lee et al. (2002) presents an empirical definition of four high-level categories of the multidimensional construct of information quality: contextual, intrinsic, accessibility and representational. Intrinsic is defined by Lee et al. (2002) as information with quality in its own right. Furthermore, Dooley (2015) states that intrinsic information quality has correctness that is innate, irrespective of the context within which the information is being utilised. Contextual is defined by Lee et al. (2002) as a requirement for information quality to be located within the task context in question, while they define representational as the need to ensure information is presented properly so that it can be manipulated and interpreted with ease, and accessibility as a computer system's importance in the storage and provision of access to secure information. Four distinct dimensions are proposed by Wang and Strong (1996) for information quality: contextual, intrinsic, accessibility and representational. Intrinsic quality represents data having value in its own right, contextual value hails from its utilisation within the task context in question, while accessibility and representational are related to the manner in which information is accessed and presented, where both the latter dimensions emphasise the system role importance. Likewise, Orr (1998) views data quality as being fundamentally intertwined with the manner in which the system fits in real-world settings. Within the literature on BI, information quality has also been considered as a key success dimension. Within a survey that assessed BI practices, Watson et al. (1997) found 79% of the BI managers stated that a primary motivating factor for the implementation of a BIS was the need for information of quality. Two empirical studies that measured the success of BISs explored information quality attributes such as consistency, accuracy and data completeness within BI (Wixom and Watson, 2001; Gable et al., 2008). Within this study, the definition of information quality that a BIS provides is the extent that a system provides accurate, consistent, sufficient and complete data and information in a timely manner (Teo et al., 2008; Liu and Goodhue, 2012).

3.2.1.3 Decision quality (user satisfaction)

User satisfaction is asserted by DeLone and McLean (2003) to be a more broadly employed measure when IS success is studied. The satisfaction is the extent to which pleasure arises through a user's interaction with an application (Doll and Torkzadeh, 1988; Seddon and Kiew, 1996). As it is difficult to directly measure the effectiveness or quality of an IS, researchers began to use indirect measures such as the measure of user information satisfaction (Seddon and Yip, 1992). Typically, user satisfaction is treated in the literature as the attitudes cultivated by users towards IS following their interaction with it (Wixom and Todd, 2005). Within the IS research field, it is fundamental to have an outcome measure that is well defined. As such, user satisfaction has traditionally been used as an IS success surrogate, with user satisfaction being utilised repeatedly in studies. Primarily, user satisfaction has been measured through a variety of subsets related to beliefs in respect to particular information, systems or other associated characteristics (Wixom and Todd, 2005). User satisfaction can be considered as a measurement of successful interaction between the users themselves and the information (Hendrickson et al., 1994). DeLone and McLean (1992) argue that there has been widespread use of user satisfaction for a number of reasons. Firstly, there is a high level of face validity with satisfaction, since it is difficult to deny that a system is successful if users assert that they like it. Secondly, the development of Bailey and Pearson's (1983) instrument and derivatives from that have offered a tool that is reliable for the measurement of satisfaction, as well as for the drawing of comparisons between studies. Thirdly, satisfaction has appeal as a measure of success, since the majority of other kinds of measures are unsatisfactory due to being weak in conceptual terms or because they are difficult to obtain empirically. Generally, satisfaction refers to an attitude that is evaluative in respect to an experience or object. Moreover, satisfaction is a behavioural response associated with the summation of the attitudes or feelings a person has towards various factors that have an effect on a situation (Bailey and Pearson, 1983). It is treated, therefore, as an overall success measure rather than being a particular success dimension (Gable et al., 2003). In addition, satisfaction is considered as a subjective system measure that may be defined as the degree that customers consider that a service is meeting their needs (Liu et al., 2016). Numerous studies have utilised user satisfaction for the variables of success with end-user computing (Doll and Torkzadeh, 1991; Ong and Lai, 2007), for data processing systems (Bailey and Pearson, 1983; Soliman et al., 2000), for e-commerce (McKinney et al., 2002; Urbach et al., 2010), and for data warehousing software (Wixom and Todd, 2005). In the context of BI, researchers have adopted user satisfaction for variables of system success (Woodside, 2011; Hasan et al., 2012; Nasab et al., 2015; Hung et al., 2016). Wixom and Todd (2005) consider that in BI contexts, user satisfaction is typically seen as the user's attitude towards BISs. Often, user satisfaction for ISs is measured through beliefs regarding information characteristics (Wixom and Todd, 2005). Numerous studies employ satisfaction for indicating acceptable performance (e.g. Galbraith, 1973; Vessey, 1991), whilst others employ success for indicating acceptable performance (e.g. Langer, 1975). An approach to the definition of decision quality is the employment of experts to identify what represents an optimum decision, as well as what comprises suitable criteria for achieving a high degree of decision quality (Ross, 1974; Jacoby, 1977).

As discussed above, the measurement of decision quality is carried out through the use of perceived user satisfaction utilising the outcomes as decision quality surrogates. Therefore, this research defines user satisfaction/decision quality as the degree to which the user of BI has satisfaction with the decision outcomes based on the BIS results (Visinescu et al., 2017).

3.3 Independent variable (implementation factors)

Implementation factors may be defined as those factors having a potential impact on BI implementation success in either a negative or a positive way (Davis and Yen, 2018). The review of the literature highlights numerous implementation factors that have a bearing on the implementation of BI, and also have a direct impact on the outcomes of implementation. In an early study of the implementation of BI, a research model was developed by Wixom and Watson (2001) that provides an explanation of the relationships between those factors having an effect on the success of a data warehouse. The implementation factors identified in the model are resources, management support, user participation, champions, development technology, source systems and team skills, with the assumption there are three stages at which they have an impact on success in implementation: the project stage, the organisational stage and the technical stage. The three implementation success stages subsequently impact on system success, as can be measured by the perceived net benefits, system quality and data quality. As per the study of Wixom and Watson (2001), the adoption of implementation factors was selected by Xu and Hwang (2007), where based on a review of previous data warehousing studies, the latter authors used eleven implementation factors to find the impact of them on system success, claiming that all the implementation factors are considered to have criticality other than those with a negative coefficient (i.e. proper planning). Thus, data warehouse success can be considered as being associated with ten major implementation factors: business benefits/needs that are clearly defined, support of top management, user participation/involvement, source data quality, adequate consultants and IS staff, proper development technology, practical implementation schedule, project management/teamwork, measurement of the business benefits and adequate funding. Ten CSFs considered necessary for successful implementation are also identified by Arnott (2008): informed and committed executive sponsor, widespread support of management, appropriate technology, appropriate team, effective data management, adequate resources, well-defined systems requirements and information, clear linkage to business objectives, and a project scope that is developed and managed in an evolutionary manner. A model of data warehouse success was also developed by Hwang and Xu (2008) by grouping the implementation factors into three categories: economic factors (measurable business benefits and adequate funding), operational factors (user participation/involvement and business benefits/needs that are clearly defined), and technical factors (proper development technology, source data quality, adequate consultant and IS staff, and project management teamwork). Yeoh and Koronios (2010) undertook an important study that sought to develop a BIS implementation framework, where the basis of their framework is the identification of CSFs and assessment of the relationships that they have with change management associated with the implementation of BI. A motivation behind their empirical research was the shedding of more light on the CSFs that influence BIS implementation. They believed that understanding the CSFs would enable stakeholders in the BI to optimise their efforts and scarce resources through concentration on those significant factors most likely to help in the successful implementation of the system (Yeoh and Koronios, 2010). A 2-stage qualitative approach was used within their research, which began with the Delphi method for the undertaking of three study rounds. Then, the framework and associated CSFs were examined by the researchers through a number of case studies. Empirical findings from the study substantiate the framework's construct and applicability, and show that organisations that address CSFs within BI implementation have more likelihood of achieving favourable results. Yeoh and Koronios (2010) also forwarded a framework for the implementation of BI with CSFs (see Figure 3.5), where the grouping suggested in the work of Wixom and Watson (2001) was used for the division of CSFs into three broad categories: technology (infrastructure and data quality), organisation (business case and vision, championship and management) and process (methodology and project management, change management and team). Woodside (2011) undertook a survey within a national organisation for healthcare that had recently experienced the completion of BI implementation, where a number of key implementation factors for the success of BI were identified. The suggestion from the survey was that customisation, a collaborative culture, resources, project management, the support of top management, vertical integration and training have a positive impact on success in BI implementation. CSFs were classified by Olszak and Ziemba (2012), who applied them into Wixom and Watson's (2001) model for data warehouse success in order to identify which are important for the implementation of BISs in small and medium-sized enterprises within the Upper Silesia region of Central Europe, with the following CSFs identified: senior management support, sufficiently skilled/qualified managers/team/staff, a competent project manager for BI/leadership, cooperation with a supplier of BI that has previous experience, adequate budget, a business vision and plan that is clear, effective change management, clear business processes and well-defined problems, expectations of users that are also well-defined, the adjustment of the BI solution to the business expectations of users, data quality, integration between the system for BI and other kinds of system, appropriate tools and technology and a BIS that is 'user friendly', BI flexibility, and responsiveness to the requirements of users. Numerous implementation factors were adopted by Hasan et al. (2012) based on their review of BI studies, with their results revealing that the following CSFs play a vital role in the achievement of success: employee participation, management support, organisation size, consultant support, organisational structure, organisational culture, government, stakeholder and competitor.

With the adoption of a holistic approach, Puklavec et al. (2014) only identified several CSFs and a procedure that is critical for implementation to be successful. They identified CSFs considered essential for implementation to be successful: perceptions with regard to strategic value, expected benefits, whether the BIS forms part of enterprise resource planning, cost, organisational culture, management support, organisational data environment, project champions, size, external support and organisational readiness. In addition, a study was undertaken by Naderinejad et al. (2014) to examine the temporal significance of CSFs during various implementation stages, where those considered most significant during implementation were goals, strategy and perspective. Besides those CSFs, others that were considered to be important were human resources, financial resources, leadership, organisational culture, methodology, process maturity, coincidence of IT and business, management support, change management, process documentation, frequent development model, project team combination, knowledge transfer speed and technology, suitable technology and infrastructure, application capability, data quality, and finally support and training. Yeoh and Popovič (2016) undertook an approach within case studies (related to seven large Australian organisations) and proposed the observed factors that were vital for success, with their work suggesting that committed support of management and sponsorship; a business case that is well-established and a clear vision; balanced team composition and business-centric championship; a development approach that is iterative and business-driven; change management that is user-oriented; a technical framework that is flexible, scalable and business-driven; and sustainable integrity and data quality all have significant, positive and direct impacts on the implementation of BISs. The sample of their research, however, only included seven firms, which suggests that caution should be exercised when the findings are implemented. A range of other factors for implementation identified from other BI literature include complexity, relative advantage, knowledge integration, compatibility, consultant ability, competitive pressure and training (Hung et al., 2016); knowledge sharing (Bach et al., 2016); continuous support, open corporate culture and the segmentation of users (Mesaros et al., 2016); metrics and professional networks (García and Pinzón, 2017); business partners and observability (Hatta et al., 2017); and regulatory compliance and external market influence (Lautenbach et al., 2017). There is, in fact, exhaustive literature in relation to implementation factors for the success of BI. Since BI is broad in nature, researchers have tended to focus on different implementation aspects. However, even though the researcher of this study’s focus is varied, certain implementation factors, as noted above, are common and have critical relevance for implementation or the strategies of implementation. Following the literature review for this study, the implementation factors cited most commonly include management support, data source systems, resources, IT infrastructure, business plan and vision, champions, team skills, project management, user participation, and change management.

Figure 3.6 (see also Appendix 1) presents the statistics of frequency for various implementation factors from investigations that attempted to offer analyses of success in BI implementation.

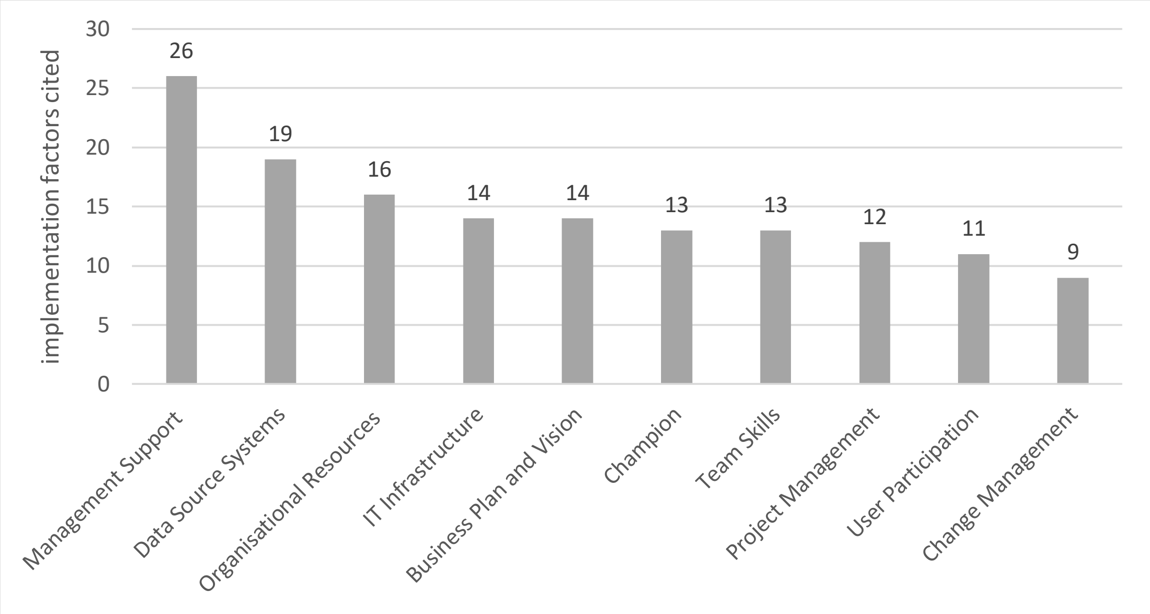

Figure 3.6 The most common implementation factors cited in the reviewed literature (Source: the author)

3.3.1.1 The gap of the implementation factors

A focus on merely technical aspects when analysing BI implementation was overcome by extending further than solely a technical rationale, with analyses of implementation factors at various aspect levels such as the process-based, project-oriented and organisational levels. From the analysis presented above in section 3.3.1, there is an evident lack of research into user effectiveness and social aspects for BI, which is another gap in the literature that has been identified. To respond to that, the primary agenda for this study is to seek to narrow the pronounced gaps discovered within the literature. Therefore, a review and comparison of prominent IS implementation models was conducted, with Petter et al.'s model (2013) appearing to be the most-cited study within the IS implementation field, where their model of IS success answered a new kind of question: if the IS success model is a reasonably robust description of the dependent variables of IS research, then what are the independent variables that influence IS success? In other words, what determinants have been shown to relate positively to IS success? Following the analysis of 140 studies of IS undertaken in a fifteen-year period, Petter et al. (2013)

discovered 43 variables that were suggested as IS success implementation factors, which were categorised into five groups: individual, task, project, organisational and social. These groups thus highlight the key factors for success that impact on IS success, as noted within the broad range of studies they analysed. Those five factors were then allocated to one of three determinant categories of success: user and social (enjoyment, attitudes toward technology, user expectations and trust), project and organisational (relationship with developers, user involvement, extrinsic motivation, management support, organisation competence, management processes and IT infrastructure) and task (difficulty and compatibility). Furthermore, prior research was undertaken on the reasons why systems were succeeding or failing. Within those studies, social IS implementation issues were seen as having importance (Bostrom and Heinen, 1977; Chen and Nath, 2008). Furthermore, a key component for system success was the involvement or relationship of system designers and users within the process of system development (Harris and Weistroffer, 2009), whereby any lack of attention paid to those relationships may result in the failure of the IS. It has been suggested by other researchers that various relevant social groupings could define technological problems in different ways, and there may be disagreement over the definitions for what would constitute failure and success (Wilson and Howcroft, 2002). Other researchers hypothesised that the organisational role or the attitude of users in respect to a new system are factors that are key in the determination of whether a system is successful (see, for example, Caldeira and Ward, 2002; Chau and Hu, 2002; Burton-Jones and Hubona, 2005; Seethamraju, 2015). A pre-eminent approach employed within most contemporary system development projects, on the other hand, is the acceptable technology experience (Agarwal and Prasad, 1999; Hackbarth et al., 2003). Within the existing literature on IS, various user factors were found to impact on the success of IS in general, including end-user training (Nelson and Cheney, 1987), gender (Simmers and Anandarajan, 2001), user conflict (Guimaraes et al., 2003), user influence (Guimaraes et al., 2003), user expertise (Guimaraes et al., 2003), peer support (Kulkarni et al., 2013), visibility (Agarwal and Prasad, 1997), attitude toward change (Caldeira, and Ward, 2002; Chau and Hu, 2002; Vakola and Nikolaou, 2005), subjective norms (Taylor and Todd, 1995; Karahanna et al., 1999), and enjoyment (Staples et al., 2002; Schmidt et al., 2004; McElroy et al., 2007). Much of the research in relation to success in IS has had a focus on the identification of those factors that are conducive to the failure or success of such systems, with those identified factors including computer anxiety/self-efficacy (McElroy et al., 2007; Karsten et al., 2012), personal characteristics (Ginzberg, 1981; Igbaria and Greenhaus, 1992; Klopping et al., 2004), user training (Nelson and Cheney, 1987), user involvement (Barki and Hartwick, 1989; Amoako-Gyampah and White, 1993) and task characteristics (Saunders and Courtney, 1985). By way of conclusion, it may be noted following comparison of the studies on the implementation of IS and BI that trust and attitudes toward technology were not included within previous studies on BI. This observation agrees with the findings of Gaardboe and Svarre (2017) following their systematic review of the literature showing a lack of social and user aspects within the models for BI implementation. In order to reduce the gap in the literature on the implementation factors of BI, this study has selected ‘attitudes toward technology’ and ‘trust’ as implementation factors that could have an effect on the success of BI. In selecting those factors, consideration is given to their relevance as probable determinates of the success of BI implementation, based on the literature reviewed.

3.4 Conceptual framework

BI success and IS success tend to be multifaceted concepts. As such, a range of models have been developed through various studies in order to ascertain the potential impact of implementation factors on the success of BI (Wixom and Watson, 2001; Hwang and Xu 2008; Hawking and Sellitto, 2010; Yeoh and Koronios, 2010; Woodside, 2011; Olszak and Ziemba, 2012; Dawson and Van Belle, 2013; Yeoh and Popovič, 2016; García and Pinzón, 2017); however, none have forwarded a model that is comprehensive to serve as a strategy for implementation that takes into account both the social and user aspects. For the development of a comprehensive and practical framework beneficial for both industry practitioners and for the body of knowledge in general, a review of existing theories was conducted and the limitations and contributions noted. Based on those theories, the key variables for implementation and success were identified, which form the foundation of this study’s conceptual framework. The review of the general literature on IS implementation success and success in BI implementation specifically served as the basis for the implementation factors identified for use in this research. As discussed above, several factors were highlighted by the author and used within the literature numerous times. Those factors play a significant role in the implementation of BI, thus offering a greater understanding of the process of BI implementation. Analyses of the aforementioned factors serve to illustrate their coverage of a wide scope of organisations within various sectors. Factors that could support the development of a conceptual framework for success in the implementation of BI within the mining sector in Jordan were selected by the author. The selection of factors by the author was carried out on the basis of the frequency that the factor occurred within the literature and its importance for success of BI. In addition, the decision was made to add two further factors from the literature on IS that were considered as having the potential to enhance the proposed model of BI implementation success. The proposed conceptual framework is presented in Figure 3.7, with the suggestion that the success of BI may be measured using three dependent variables developed by DeLone and McLean (1992, 2003): system quality, information quality and user satisfaction/decision quality. The proposed conceptual framework for this research suggests that the success of BISs is affected by twelve independent variables or implementation factors: business plan and vision, management support, champions, resources, project management, team skills, change management, data source systems, IT infrastructure, attitudes toward technology, trust and user participation. The success of the BIS is represented by three dependent variables, two variables representing system success (i.e. system quality and information quality) and one variable representing the effectiveness of the system success (i.e. decision quality). Consequently, this research aims to undertake an investigation into the impact of system quality on information quality, and the impact of the success of the system (i.e. information and system quality) on decision quality. There are also twelve indirect effects hailing from the implementation factors impacting on information quality suggested by the conceptual framework by way of system quality, and the indirect effect on decision quality from system quality by way of information quality.

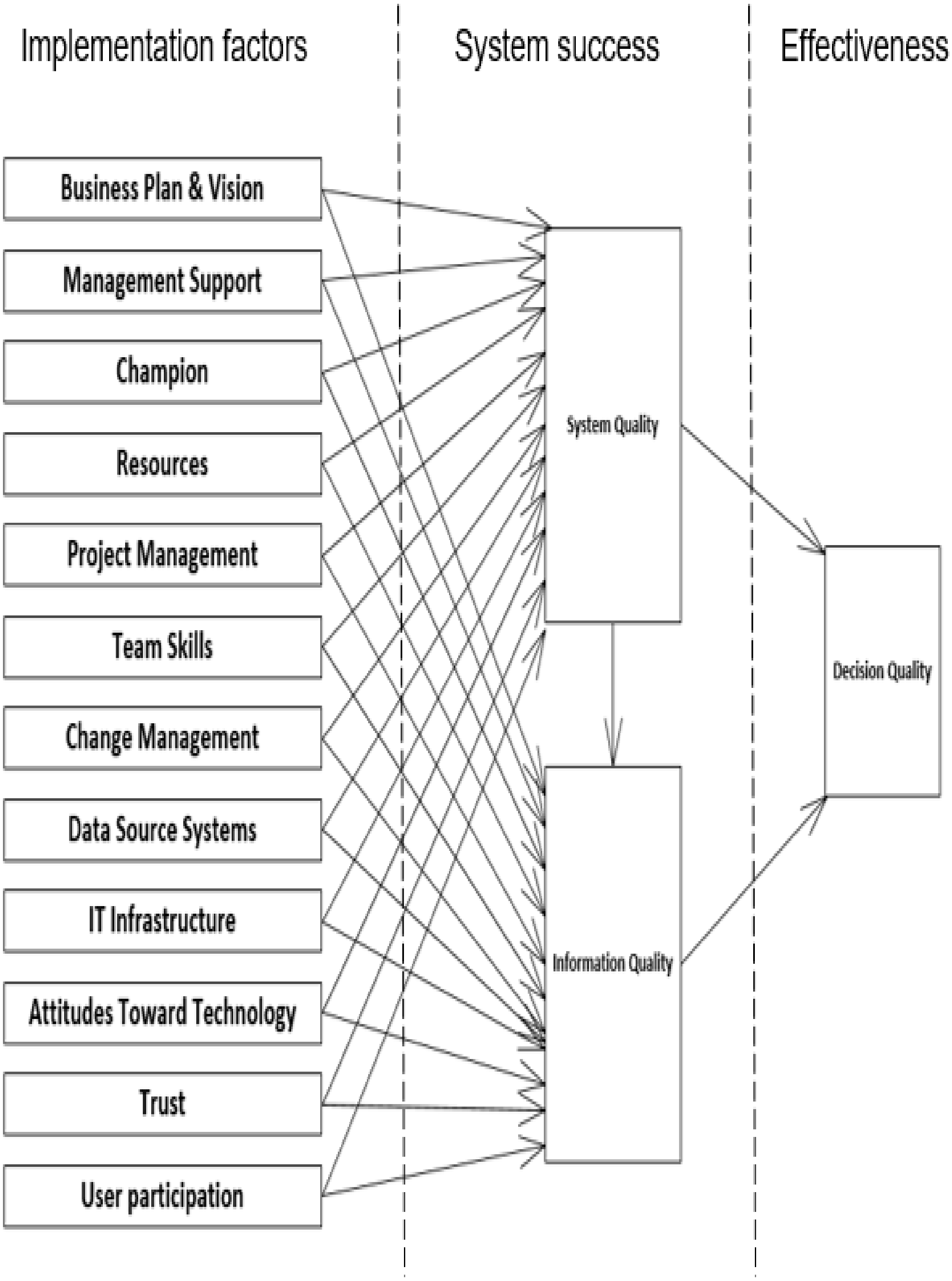

Figure 3.7 Conceptual framework for BI implementation success (Source: the author)

3.5 Hypothesis development

This study conducts an investigation of the impact of BI implementation factors, namely business plan and vision, management support, champions, resources, project management, team skills, change management, data source systems, IT infrastructure, attitudes toward technology, trust and user participation. For BI success, system quality lies at the technical level whilst information quality lies at the semantic level. In addition, the research investigates the impact of the success of BISs upon decision-making quality at the effectiveness level within the Jordanian mining sector. In order for the investigation to be facilitated, several hypotheses are developed, and this development process is discussed in the paragraphs that follow.

- **Business plan and vision and business intelligence success**

If the business plan and vision are clear, an organisation can be helped in strategising its missions. Furthermore, the dissemination of the organisational vision is required throughout the different levels of the organisation (Nah and Delgado, 2006). Loh and Koh (2004) assert that it is essential to have both a suitable vision and business plan for the delineation of the projected advantages (both tactical and substantial), the costs, risks, resources and timeline. Meanwhile, Nah and Delgado (2006) argue that doing so supports the maintenance of a focus on the business benefits for an organisation. An organisation is aided by a business plan that is clearly focused on the benefits to the business, with ongoing guidance for the implementation efforts in the organisational system (Yeoh and Koronios, 2010). Mungree et al. (2013) state that a project ought to align with the business and have system requirements that are clearly defined, while Boonsiritomachai et al. (2014) propose that a needs analysis for the vision, requirements and business ought to be undertaken prior to the implementation phase. A clear vision helps organisations to strategise their missions, and has to be communicated across all organisational levels (Reich and Benbasat, 2000). It is thus vital to have apparent goals, objectives and business visions in place for projects of BI implementation (Puklavec et al., 2014). Adamala and Cidrin (2011) note that BISs have to be closely tied with the strategic company vision, since a clear vision enables the successful implementation of BI projects. Moreover, a long-term vision in respect to strategy and organisation is vital for the establishment of robust businesses aligned to the strategic vision so that the objectives and needs of business can be reached (Yeoh and Koronios, 2010). Within this study, business plan and vision have been defined as the clear business plan, vision and objectives aligned with the strategies, goals, mission and objectives of the company. Moreover, a business plan should contain quantified objectives and goals, as well as detailed strategies and action plans in support of the direction of the company (Kearns and Sabherwal, 2006). Numerous studies have demonstrated that BIS success is considerably influenced by a clear vision (e.g. Arnott, 2008; Yeoh et al., 2008a; Yeoh et al., 2008b; Yeoh and Koronios, 2010; Dawson and Van Belle, 2013; Sangar and Iahad, 2013; Nasab et al., 2015; Yeoh and Popovič, 2016). Hwang and Xu (2008) showed empirically that the needs of the business and a clear vision impact on system quality in a significant and positive manner. Furthermore, a study undertaken by Pham et al. (2016) discovered that a significant relationship exists between BI success and the business plan and vision. A significant impact on BI success was also found to result from the business plan and vision by Rezaie et al. (2017). Therefore, based on the discussions above, the following hypotheses are proposed:

H1a: *Business plan and vision have a positive effect on system quality*

H1b: *Business plan and vision have a positive effect on information quality*

- **Management support and business intelligence success**

The most widely cited implementation factor is management support, which reflects the degree of support offered by the management in the promotion, sponsorship and/or championing of IS use, in addition to the willingness of ensuring that adequate resources are allocated (Petter et al., 2013). Executive or management support enables the required capital to be provided smoothly, along with adequate human resources and ensuring other internal related resources required for the implementation of BI are available and coordinated (Hawking and Sellitto, 2010; Anjariny and Zeki, 2013). Furthermore, the implementation of BI ought to be 'business-driven', involving the widespread support of the management (Arnott, 2008). The management support is a factor that is essential for successfully implementing BI as there is a direct impact on resource allocation to the project, in addition to the impact on the user's perspectives. Furthermore, since the expectations of senior management have an impact on the attitudes towards the importance of implementation (Boyton et al., 2015), the management of the process of change can be supported and resistance overcome. Gaining commitment in an organisataion and the commitment from managers may also be considered as a key challenge that is faced by a team tasked with BI implementation (Yeoh et al., 2008). Olbrich et al. (2011) note that strong management support is the most important factor for BI success, whilst also highlighting its controllability; however, management support can, over time, vary quite considerably. Furthermore, BI may be transformed by the management's organisational strategy (Olszak and Ziemba, 2012). In this research, management is defined as leaders and management that demonstrate strong commitment and support to the project for BI through their active interest in the problems encountered and the provision of the required resources, along with encouragement for the use of the system of BI (Igbaria et al., 1997; Klein et al., 2001; Wixom and Watson, 2001). Overall success of the system in BI implementation is significantly affected by the support of management (Arnott, 2008; Yeoh et al., 2008a; Yeoh et al., 2008b; Yeoh and Koronios, 2010; Woodside, 2011; Olszak and Ziemba, 2012; Anjariny and Zeki, 2013; Dawson and Van Belle, 2013; Sangar and Iahad, 2013; Puklavec et al., 2014; Grublješič and Jaklič, 2015; Nasab et al., 2015; Acheampong and Moyaid, 2016; Mesaros et al., 2016; Pham et al., 2016; Yeoh and Popovič, 2016; García and Pinzón, 2017; Lautenbach et al., 2017; Rezaie et al., 2017; Puklavec et al., 2017). Management support also affects other BI success variables such as system use (Xu and Hwang, 2007), organisational implementation (Wixom and Watson, 2001), user satisfaction (Hung et al., 2016) and productivity and decision-making (Hasan et al., 2012). Hwang and Xu (2008) found management support to positively and directly influence system quality, but not information quality. In the empirical work of Owusu et al. (2017), however, management support does not influence BI success. It is considered overall that effective BI implementation cannot be achieved if sufficient support is not offered by the management. Thus, the following hypotheses are forwarded:

H2a: *Management support has a positive effect on system quality*

H2b: *Management support has a positive effect on information quality*

- **Champions and business intelligence success**

The necessity of a project champion is also thought to be a factor that is relatively significant in the successful implementation of BI. As noted by Mandal and Gunasekaran (2003), the champion of a project should have strong leadership skills. Furthermore, a project champion should have managerial competencies in a variety of technical, business-oriented and personal dimensions (Kraemmergaard and Rose, 2002). The definition for a project champion here is a management-level individual who recognises when an idea is useful for their organisation, and then leads with sufficient resources and authority during all development and implementation phases (Meyer, 2000). The champion is defined by Wixom and Watson (2001) as an individual within an organisation who actively promotes and supports a project and provides political support, material resources and information. Yeoh and Koronios (2010) describe a champion as an individual with a high degree of enthusiasm and deep knowledge of the processes for business in their organisation, as well as commitment and sound awareness of those technological innovations being discussed. There is a tendency for champions to be managers at the mid-level of organisations who have the goal of building local initial successes in BI so that executive support can be attracted for BI implementation that is more enterprise-wide (Davenport and Harris, 2007). The main concern of the champion is thus organisational. Moreover, it is recognised that for the support of top management to be obtained, a champion has to also provide effective support to the process of BI through, for instance, the provision of access to data, information, political support and material resources (Davenport and Harris, 2007; Dawson and Van Belle, 2013). champions provide support through their 'people skills' and the drive for more data and analyses, the teaching of others, their awareness of BI's limitations, focusing efforts for BI on those areas where the most difference will be made, and so on (Davenport et al., 2010). Within this research, the definition of the champion is a person in an organisation who has an understanding of BI potential, the ability and power to encourage a project team to promote a personal BI project vision in an active and vigorous manner, and who is able to ensure that project tasks will be completed (Lim et al., 2000; Kayworth and Leidner, 2001; Wixom and Watson, 2001). The existing research in the field reveals that when project champions are present, they are capable of impacting significantly on the successful adoption of BISs (Arnott, 2008; Yeoh et al., 2008a; Yeoh et al., 2008b; Yeoh and Koronios, 2010; Olszak and Ziemba, 2012; Anjariny and Zeki, 2013; Dawson and Van Belle, 2013; Sangar and Iahad, 2013; Puklavec et al., 2014; Nasab et al., 2015; Acheampong and Moyaid, 2016; Pham et al., 2016; Yeoh and Popovič, 2016; García and Pinzón, 2017; Rezaie et al., 2017; Puklavec et al., 2017). Furthermore, Owusu et al. (2017) found that a strong relationship exists between BI success and the project champion, although support for that relationship was not found in the study of Wixom and Watson (2001). The following hypotheses are thus proposed for this study:

H3a: *Champions have a positive effect on system quality*

H3b: *Champions have a positive effect on information quality*

- **Resources and business intelligence success**

Grandon (2004) clarifies that 'project resources' refer to the extent of finanical, human and technical resources available in a project for the implementation of a system. Puklavec et al. (2014) explains that BISs have a tendency to involve greater degrees of action of a voluntary nature, resulting in increased sensitivity in respect to the availability of resource that have significance for BIS adoption. In addition, the project for BI comprises a group of processes and activities that bring together material and human resources for the creation of a service or product that meets the objectives in respect to cost, performance, quality and the schedule (Fedouaki et al., 2013). Furthermore, successful BISs evolve as a response to the dynamic requirements of business, by way of an iterative developmental process, where that evolution requires consistent and ongoing resource allocation (Arnott and Pervan, 2005). Resources are not only necessary to support technical development and acquisitions, but also to overcome the likely organisational challenges that manifest with expansion of the system and the 'ripple effect' of system use in other units of the business (Yeoh et al., 2008b). Emam (2013) argue that the planning and scoping of BI ought to be adaptable and flexible to allow changes to the requirements within the resources of the budget and the timeframe. Within this research, the resources factor of the project is defined as time, people and the finance needed for successful implementation of the BI project (Wixom and Watson, 2001). Owusu et al. (2017) suggest that the enhancement of organisational resources could impact on BIS implementation, with this view supported by the work of Wixom and Watson (2001), Arnott (2008), Yeoh et al. (2008a), Yeoh et al. (2008b), Yeoh and Koronios (2010), Woodside (2011), Dawson and Van Belle (2013), Boonsiritomachai et al. (2014), Puklavec et al. (2014), Grubliešič and Jaklič (2015), Acheampong and Moyaid (2016), Salmasi et al. (2016), Yeoh and Popovič (2016), Hatta et al. (2017), and Rezaie et al. (2017), amongst others. All of these studies help in terms of highlighting the positive and direct impacts that the organisational resources have on overall BIS success. Other BI success variables impacted by project resources include project implementation and organisation (Wixom and Watson, 2001), as well as productivity, information quality and system use (Xu and Hwang, 2007); however, Hwang and Xu (2008) report that project resources impact on system quality positively and directly, but not information quality. Therefore, the following hypotheses can be put forward:

H4a: *Resources have a positive effect on system quality*

H4b: *Resources have a positive effect on information quality*

- **Project management and business intelligence success**

The terms 'project management' refers to the ongoing management of the implementation plan. In addition to the planning stages, it involves the allocation of responsibilities to various stakeholders, as well as identifying the milestones and critical paths, the planning of human resources, training and the determination of indicators of success (Nah and Delgado, 2006). Newell and Grashina (2004) suggest that the traditional project management triangle offers the ability to assess the requirement delivery for project scope (integration and function), timescale and budget. If these goals are reached, a conclusion can be drawn that the implementation has been successful. A systematic approach may be offered through the project management of all of the project stages by ensuring that there is careful planning, monitoring and measuring of each step. Initially, it was intended that modern methods of project management were applied within large organisations with complex systems requiring systematic processes (Baccarini, 1999); however, in recent years such methods can be modified in order to make them appropriate for addressing requirements in smaller organisations (Fedouaki et al., 2013). The recommendations of Rezaie et al. (2017) note that the implementation of BI has intricacy, with a need for the grouping of proficiencies in change, business and technological management. In order to avoid failure and to achieve the desired gain and benefits, project managers must manage cautiously while monitoring the entire process of BI implementation (Arnott, 2008; Anjariny and Zeki, 2013). Project management skills, therefore, have significance and are perhaps essential for BI implementation success. Indeed, for successful project implementation, project managers require skills in the roles related to both tactical and strategic project management. Pham et al. (2016) note that project management relates to the planning and organisation of system implementation, as well as the acquisition of IS, the selection of a suitable workforce and appropriate administration and oversight. Meanwhile, Bach et al. (2016) emphasise that for the delivery of BI success, project management is vital. In that respect, it has been argued that due to the impact of BIS, individuals employed within a project team ought to hail from management or have an administrative role, as well as having active involvement in decision-making (Emam, 2013; Fedouaki et al., 2013; Boyton et al., 2015; Gaardboe et al., 2017). Within this research, the definition for project management is that of a team with a willingness to assess the performance of a project in the early implementation stages, as well as having responsibility for the measurement of the performance in terms of the implementation and acquisition of control for the process, and having the ability to communicate to all the relevant team members (Grover et al., 1995). As noted by numerous authors, project management may impact considerably on BIS implementation (Arnott, 2008; Yeoh et al., 2008a; Yeoh et al., 2008b; Yeoh and Koronios, 2010; Woodside, 2011; Anjariny and Zeki, 2013; Sangar and Iahad, 2013; Pham et al., 2016; Rezaie et al., 2017). Hwang and Xu (2008) report, however, that the resources of a project impact positively and directly on information quality, but not on system quality. Therefore, the following hypotheses are proposed for this research:

H5a: *Project management has a positive effect on system quality*

H5b: *Project management has a positive effect on information quality*

- **Team skills and business intelligence success**

BI implementation requires interpersonal abilities and technical skills in a team, and the capacity to skilfully undertake tasks to ensure good interaction amongst users (Wixom and Watson, 2001). Moreover, a project team should consist of members hailing from a variety of areas in a business so that ideas can be shared and the potential for standardisation can be increased, especially if, as an aspect of the BI initiative, there is a plan for an enterprise-wide data warehouse (Alshawi et al., 2011). García and Pinzón (2017) argue that the implementation of BI ought to be primarily through a project that is business-driven, as opposed to technologically-driven. However, if the relevant skills are unavailable in a firm, they may have to be externally sourced through the use of consultants (Anjariny et al., 2012). The stimulation of learning and innovation arises through team members coming together from a diversity of competencies and perspectives, which may lead to a wider range of alternative solutions being generated to help address complex problems (Campion et al., 1993; Lee and Xia, 2010). Within this research, skills are defined as the interpersonal and technical abilities of BI members (Wixom and Watson, 2001; Lee and Xia, 2010). Skills within a team have a significant impact on the overall success in BI implementation (Arnott, 2008; Yeoh et al., 2008a; Yeoh et al., 2008b; Yeoh and Koronios, 2010; Olszak and Ziemba, 2012; Anjariny and Zeki, 2013; Sangar and Iahad, 2013; Nasab et al., 2015; Mesaros et al., 2016; Yeoh and Popovič, 2016; García and Pinzón, 2017; Rezaie et al., 2017). Skills within a team also impact on other BI success dimensions such as project implementation, productivity, information quality and decision-making (Wixom and Watson, 2001; Xu and Hwang, 2007; Hwang and Xu, 2008). Hwang and Xu (2008) report, however, no impact on system quality from team skills, although they argue that team skills have an impact on the information quality that a BIS provides. A significant relationship between BI success and team skills was also not found in the work of Hatta et al. (2017). It can be hypothesised, therefore, that:

H6a: *Team skills have a positive effect on system quality*

H6b: *Team skills have a positive effect on information quality*

- **Change management and business intelligence success**

Change management refers to the procedures for the management of change within an organisation. Such changes both revolutionise and reinvent the processes of the government functions (Ndou, 2004). The implementation of the new system or BI forms an element of business process realignment or corporate restructuring. In such cases, the implementation of BI is seen as a change management project, with the project managed as a kind of incremental transformation or change (García and Pinzón, 2017). The management of organisational inertia with regard to the acceptance of change and the associated conflicts is an initial priority for top levels of management within a business scenario of this kind (Fedouaki et al., 2013). Methodologies, processes and activities that may support the issues of employees with regard to change and the implementation of BI are prioritised (Naderinejad et al., 2014). Company processes and structures prior to the change are potentially incompatible with the changes or improvement intended through the BI. In these cases, there are advantages to the adoption of the implementation of BI as a process of change management (Boyton et al., 2015; García and Pinzón, 2017), where it may be vital to distinguish the need for change in order to remain competitive. Within this study, the definition for change management is a process by which organisations and individuals are transformed into a desired state through support for users and an implementation team, along within consultations related to the problems encountered whilst the implementation is ongoing. Change management programmes have importance as they enable potential resistance to implementation to be reduced, and thus they help adoption to be facilitated (Hawking and Sellitto, 2010), particularly when technological development is being undertaken as there is a greater likelihood for change to arise during this phase (Fourati-Jamoussi et al., 2016; Garcia and Pinzon, 2017). A factor that may be absent in successful BI delivery is change management within process improvement, with Williams and Williams (2007) revealing that process engineering serves as a foundation for delivery management to add value to a business. Furthermore, they note that with that factor lacking (i.e. an absence of the effective management of change from the processes of BI implementation), this could help to explain why BI projects fail (Williams and Williams, 2007). Several studies offer support to that notion (e.g. Yeoh et al., 2008a; Yeoh et al., 2008b; Yeoh and Koronios, 2010; Sangar and Iahad, 2013; Grublješič and Jaklič, 2015; Yeoh and

Popovič, 2016; García and Pinzón, 2017; Rezaie et al., 2017), indicating a positive and direct impact on BIS implementation from change management. Therefore, the following hypotheses are proposed for this research:

H7a: *Change management has a positive effect on system quality*

H7b: *Change management has a positive effect on information quality*

- **Data source systems and business intelligence success**

The sources of data can be defined as those places where the data that is employed within analyses are kept and accessed for utilisation (Hostmann et al., 2007). A system source is a data source for a BI. A system could operate due to its own particular qualities, without association to anything else, or it could serve as a telemetry point or electronic data feed (Adamala and Cidrin, 2011; Bargshady et al., 2014). Previous research has discovered that the quality of the existing data of an organisation may profoundly affect the initiatives of systems, and companies may realise considerable benefits through improved data management (Wixom and Watson, 2001). A benefit hailing from BI is the integration of data throughout an organisation, since it is often the case that the data resides within heterogeneous and diverse sources. There is a need for specialised technical and functional experts for each unique source in order for there to be coordination, definition and design of the data access to automate the provision of data (Wixom and Watson, 2001). Data sources utilised for information retrieval are technological capabilities of BI that could be either internal or external (Harding et al., 2006). Typically, BI has been reliant on data that is structured and/or numerical, measurable on a numerical scale and that can undergo analysis via computing equipment and/or statistical methods (Baars and Kemper, 2008). There are a growing number and variety of data sources with a relationship to BI within many organisations; however, this imposes increasing pressure on the integration of the different systems from where the data are sourced (Isik et al., 2013). Within this study, data source systems are defined as being source system quality with respect to its readiness, standardisation and disparity in the provision of data to a system of BI (Wixom and Watson, 2001). Yeoh et al. (2008) summarise that assurance of the data quality and integrity from those sourced systems impacts markedly on the success of BI implementation.

Furthermore, source system data quality has an effect on BI quality, which is the reason for its significance as a factor for BI implementation success (Puklavec et al., 2014). Several studies support this idea and reveal that data sources impact directly and positively on BI implementation success (Wixom and Watson, 2001; Xu and Hwang, 2007; Arnott, 2008; Yeoh and Koronios, 2010; Olszak and Ziemba, 2012; Anjariny and Zeki, 2013; Dawson and Van Belle, 2013; Grublješič and Jaklič, 2015; Nasab et al., 2015; Mesaros et al., 2016; Pham et al., 2016; Salmasi et al., 2016; Yeoh and Popovič, 2016; Rezaie et al., 2017; Puklavec et al., 2017). Furthermore, Hwang and Xu (2008) found that the data source system only has significance for the information quality of the BI. Işık et al. (2013) discovered the data source system to have significance as a factor of implementation within BIS success, while Hasan et al. (2012) argue that the relationship between BI success and the data source system is insignificant in statistical terms. Lautenbach et al. (2017) also found that the system of data sources does not have an impact of any significance on BI success. These results support the forwarding of following hypotheses:

H8a: *Data source systems have a positive effect on system quality*

H8b: *Data source systems have a positive effect on information quality*

- **IT infrastructure and business intelligence success**

The term 'IT infrastructure' refers to the ability for users to be given data and information at an appropriate level of timeliness, reliability, confidentiality, security and accuracy, as well as the capability of tailoring processes to align with the emerging directions and needs within the business, together with the provision of connectivity and universal access of sufficient reach and range (Fink et al., 2017). Wixom and Watson (2001) define IT infrastructure as the software methods, the hardware and the programs utilised in the completion of the implementation of a project. Within this study, the definition of IT infrastructure is a company's capability for the provision of appropriate software, hardware, and database and network technologies prior to the implementation of a BIS (Karimi et al., 2007). There are several characteristics that a BIS has in common with more traditional lifecycles of development for IT projects and their range of phases (Moss and Atre, 2003);

however, as noted by Olszak and Ziemba (2007), the undertaking of BI implementation has greater complexity and there is a need for appropriate infrastructure and resourcing over a longer period of time. The authors also remark that the implementation of BI is similar in some facets to IT infrastructure projects such as enterprise resource planning systems (Olszak and Ziemba, 2007). BIS implementation does not just involve the purchase of combinations of software and hardware, but also much greater complexity including the need for appropriate infrastructure and resourcing over a longer timeframe (Yeoh and Koronios, 2010). Furthermore, the IT infrastructure utilised by a project team may have an influence on the effectiveness of the development effort to the same extent as other types of factors such as the people involved. The effectiveness and efficiency of a development team can be impacted by the tools, particularly when those tools are not easy to use or to fully understand (Wixom and Watson, 2001). If tools are immature or overly complicated, a BI can become flawed, unreliable or problematic. Therefore, the development technology is a significant factor for BI success. Several authors have noted that the infrastructure of IT directly impacts on the success of BI implementation (e.g. Arnott, 2008; Yeoh et al., 2008a; Yeoh et al., 2008b; Yeoh and Koronios, 2010; Olszak and Ziemba, 2012; Nasab et al., 2015; Pham et al., 2016; Yeoh and Popovič, 2016; García and Pinzón, 2017; Lautenbach et al., 2017). Xu and Hwang (2007) discovered, however, that the IT infrastructure does not directly impact on system quality. The work conducted by Wixom and Watson (2001) provides confirmation of a positive relationship between technical implementation and IT infrastructure, while IT infrastructure was found by Salmasi et al. (2016) to strongly predict the success of BI. A strong relationship was also found between BI success and IT infrastructure by Rezaie et al. (2017). Therefore, the following hypotheses are proposed for this research:

H9a: *IT infrastructure has a positive effect on system quality*

H9b: *IT infrastructure has a positive effect on information quality*

- **Attitudes toward technology and business intelligence success**

The attitudes of users towards a system of IS relates to whether the perceptions of the individuals towards the system are favourable or unfavourable (Karahanna et al., 1999). Within the implementation of an IS system, there ought to be the participation of users during all implementation phases (Lassila and Brancheau, 1999); however, this research defines attitudes taken towards technology as the extent to which users possess a favourable perspective on the use of the BIS (Venkatesh et al., 2003; Kim, 2009). A significant factor in the generation of user participation is the attitude of the users. Guimaraes et al. (1996) assert that for a sustainable, effective IS system, users ought to maintain positive attitudes towards the system. Therefore, in order to render IS systems more effective, there needs to be study of the attitudes of users towards those systems. Furthermore, organisational productivity cannot be increased by IT systems alone as a system is dependent upon how people use it (Lee et al., 2017; Özdemir, 2017). Nitsch and Glassen (2015) note that supportive attitudes of users towards technology were revealed as having a positive impact on new IT system adoption. The initial attitudes of users towards BIS are critical, since they can have an impact on quality and productivity, or the extent to which there is usage of a system (Kerschner and Ehlers, 2016). Al-Jabri and Roztocki (2015) found that relationships exist between the attitudes of users towards technology and the success of an IS system; however, Tussyadiah et al. (2017) discovered that attitudes toward technology have an insignificant impact on the quality of IS systems. Therefore, this study hypothesises that:

H10a: *Attitudes toward technology have a positive effect on system quality*

H10b: *Attitudes toward technology have a positive effect on information quality*

- **Trust and business intelligence success**

Trust is identified in various IS-related studies as a primary enabler of understanding system implementation and usage (Nicolaou and McKnight, 2006). Moorman (1993) defines trust as a willingness for reliance on a partner of exchange who one has confidence in. Moreover, trust can be described as the degree of emotional security experienced by employees, and that they have in professional dealings and relationships. When there is the existence of high levels of trust, the easier emergence of novel ideas may occur. Learning and lateral thinking are encouraged when communication is shared and open (Li et al., 2008). Within this research, the definition for trust is the extent of emotional safety experienced by BI users in relation to the information and transactions provided by the system of BI (Cyr et al., 2009). Vance et al. (2008) state that if the management of a project successfully promotes relationships of trust for IS users, assures security in the business and personal information of IS users, and succeeds in providing information that is accurate and up-to-date, then the willingness of users to utilise the IS services can be guaranteed. Furthermore, Allen et al. (2000) suggest that there cannot be successful fulfilment of IS adoption unless trust exists amongst the users. In the use of the functions of IS, trust is also an important driver, whether in relation to the provision of services or the establishment of interactions amongst users of a system and improvement of the system's reputation (Grimsley and Meehan, 2007). Furthermore, it is recognised that the trust held in a system is a key driver for the implementation of IS (Hasan and Abuelrub, 2008; Horsburgh et al., 2011). Dutton et al. (2005) argue that the level of accountability and confidence of users that personal information will not be misused by the system helps to increase their trust in IS. Whilst technology use may improve the control of the information in the system, technological innovations alone are not sufficient for trust to be engendered, and thus further efforts are required for such concerns to be eased by, for example, enhancing the perceptions of the users in terms of the trustworthiness of the system (Cho et al., 2019). Thus, the following hypotheses are proposed for this research:

H11a: *Trust has a positive effect on system quality*

H11b: *Trust has a positive effect on information quality*

- **User participation and business intelligence success**

In relation to the development of particular IS, Kearns and Sabherwal (2006) consider the term 'user participation' to refer to the tasks, assignments or behaviours that users or representatives of users undertake during the project for the development of IS. User participation is defined by Barki and Hartwick (1989) as the behaviour of users of a system that is observable within the process of IS development, namely, system user participation within the activities of the development and implementation of IS. Good participation ensures that there is accurate communication and capture of the requirements of users amongst the project team members, with those properties specifically important if, initially, there is an absence of clarity in respect to the requirements of the system (Wixom and Watson, 2001). The practice of user participation is defined within this research as those activities that are undertaken during BIS implementation (Ravichandran and Rai, 1999). Audzeyeva and Hudson (2016) note the likelihood of a contribution to future usability in the long term with sufficient user involvement to adjust to the BI, in addition to it aiding in the matching of the system to other organisational processes. Furthermore, with organisational change enabled through BI there may, in turn, be support for the introduction of procedural changes to the control and coordination of the organisation. Generally, user participation is hugely significant in IS project implementation (Bano et al., 2018). User participation is also highly significant for the success of BISs (Wixom and Watson, 2001; Xu and Hwang, 2007; Hwang and Xu, 2008; Yeoh et al., 2008a; Yeoh et al., 2008b; Koronios, 2010; Dawson and Van Belle, 2013; Grublješič and Jaklič, 2015; Nasab et al., 2015; Mesaros et al., 2016; Yeoh and Popovič, 2016; Rezaie et al., 2017). Other BI success variables are impacted by management support, namely, the making of decisions (Hasan et al., 2012); productivity (Hasan et al., 2012); system use, productivity and information quality (Xu and Hwang, 2007); user satisfaction (Hung et al., 2016); and project and organisational implementation (Wixom and Watson, 2001). Xu and Hwang (2007) argue, however, that system quality is affected by user participation, but with no impact on information quality. Therefore, in this research, the following hypotheses are proposed:

H12a: *User participation has a positive effect on system quality*

H12b: *User participation has a positive effect on information quality*

- **System quality and information quality**

Generally, the quality of BI can be employed to represent system quality. Overall, if BI quality is lower, the costs are high because the BI is not serving its intended purpose (i.e. not designed as per the specifications, not robust, prone to errors, and having few provisions for security) (Hwang and Xu, 2008). Thus, low quality BI leads to a low level of information quality due to the information being incomplete, inaccurate or irrelevant. Moreover, with a flexible system there can be quick and easy modification so that changes in user information needs can be met efficiently and quickly, which results in the information output for users being up-to-date information and relevant (i.e. high information quality) (McKnight et al., 2017). Gorla et al. (2010) consider that a system that is up to date and well integrated provides accurate and complete information, and thus such outputs of information will have use in the daily tasks of users. Furthermore, studies of BIS by Wixom and Watson (2001), Xu and Hwang (2007) and Hwang and Xu (2008) discovered a strong and positive relationship between information quality and the system quality of BI. From the above findings, the following hypothesis is proposed for this research:

H13: *System quality has a positive effect on information quality*

- **Business intelligence system success (system and information quality) and decision quality**

It was found that information quality and system quality are significant predictors of decision quality/user satisfaction for IS (DeLone and McLean, 2003; Iivari, 2005). The literature discusses the importance of the success of the system and information use within decision-making quality (Raghunathan, 1999; Popovic 2012; Janssen et al., 2017). Meanwhile, Negash (2004) forwards the argument that systems for BI are introduced in order to improve the quality and timeliness of information that inform the process of decision-making. Other research by Rouhani et al. (2018) found a positive relationship between the quality of decision-making and BIS availability, while Turpin and Marais (2004) and Parnell et al. (2019) suggest that decision-makers employ support technology infrequently when making their decisions. Significant path coefficients between user satisfaction and system quality, and between user satisfaction and information quality, were reported by Rai et al. (2002). Nevertheless, the relationship between user satisfaction and information quality is supported strongly within the literature (Iivari, 2005; Ozdemir and Hewett, 2010). Meanwhile, Bantel and Jackson (1989), Amason (1996), Wixom and Watson (2001), Xu and Hwang (2007), Hwang and Xu (2008) and Visinescu et al. (2017) all show that information quality directly influences the decision-making quality, and that information quality impacts positively upon decision quality. Within this study context, there is value in exploring whether these two variables—

information and system quality—also have a positive influence on decision-making quality. Therefore, following hypotheses are forwarded:

H14: *Information quality has a positive effect on decision quality*

H15: *System quality has a positive effect on decision quality*

All of the aforementioned hypotheses are summarised below in Table 3.1. The initial 24 hypotheses relate to the implementation factors' impact on BI success, whilst the final three relate to variables for BI success.

Table 3-1 Summary of the research hypotheses

No.	Hypothesis
H1a	Business plan and vision have a positive effect on system quality
H1b	Business plan and vision have a positive effect on information quality
H2a	Management support has a positive effect on system quality
H2b	Management support has a positive effect on information quality
H3a	Champions have a positive effect on system quality
H3b	Champions have a positive effect on information quality
H4a	Resources have a positive effect on system quality
H4b	Resources have a positive effect on information quality
H5a	Project management has a positive effect on system quality
H5b	Project management has a positive effect on information quality
H6a	Team skills have a positive effect on system quality
H6b	Team skills have a positive effect on information quality
H7a	Change management has a positive effect on system quality
H7b	Change management has a positive effect on information quality
H8a	Data source systems have a positive effect on system quality
H8b	Data source systems have a positive effect on information quality
H9a	IT infrastructure has a positive effect on system quality
H9b	IT infrastructure has a positive effect on information quality
H10a	Attitudes toward technology have a positive effect on system quality
H10b	Attitudes toward technology have a positive effect on information quality
H11a	Trust has a positive effect on system quality
H11b	Trust has a positive effect on information quality
H12a	User participation has a positive effect on system quality
H12b	User participation has a positive effect on information quality
H13	System quality has a positive effect on information quality
H14	Information quality has a positive effect on decision quality
H15	System quality has a positive effect on decision quality

3.6 Chapter summary

This chapter has detailed the development of the conceptual framework with associated hypotheses. Firstly, the background to the study in theoretical terms was stated, with discussion of those theories that underpin the framework proposed. Following this, there was an examination of the various variables for IS success identified from previous research, with an explanation of the process by which the possible variables for success were selected. This examination provided the suggestion that success in BI may be measured through the use of three different dependent variables, as noted in the work of DeLone and McLean (1992), namely, quality of information, quality of system and quality of decision (user satisfaction). Then, a gap within the literature was identified in relation to the paucity of theoretical models related to the implementation and success of BI. The literature review showed identified numerous models for the implementation of BI, providing understanding of the principles underpinning BI success. The factors for BI implementation that were most commonly cited and considered to be highly significant for the implementation of BI were found to include business plan and vision, management support, champions, resources, project management, team skills, change management, data source systems, IT infrastructure, and user participation. There was also discussion with regard to additional factors related to implementation that were included in the research model, with the new variables of trust and attitudes toward technology considered as potentially affecting the success of BI. Based on the background in theory put forward within this research, and the awareness of previous relevant research, 27 research hypotheses were developed to explain each implementation factor’s effect on BI success. In the following chapter, the research methodology employed in this study in order to meet the study aim and objectives is presented.

Chapter Four: Research Methodology

4.1 Introduction

A conceptual framework was developed within the previous chapter for the analysis of the effects between the implementation factors and the success of BI. This chapter provides an overview of the research philosophy, the research design and the research methods employed in the collection and analysis of the data. It commences by identifying the bases for the concept and philosophy behind the research (section 4.2). Then, in section 4.3 an overview is presented of the underlying approach to the research with justification of the approaches selected, and an outline of the strategy and design employed for this study in section 4.4. Moving on, this chapter considers the research design in section 4.5, with justification as to why a quantitative method was selected for this study. After that, section 4.6 describes the procedures for the collection of data, including a description of the development of the scales of measurement, before an explanation of the procedures and techniques related to the analysis of the data (section 4.7) and consideration of ethical matters salient to the research (section 4.8). Finally, the conclusions are provided in section 4.9 as a chapter summary.

4.2 Research philosophy

When designing a piece of research, a starting point is the assessment of the particular philosophical assumptions being brought to the project, and then to give consideration to the selection of an appropriate methodology and the identification of suitable methods (Creswell and Creswell 2017). The term ‘philosophy’ refers to a field of study and reflection on the views, thinking, perspectives on life and how practical daily problems ought to be handled (May and Williams, 2002). A research philosophy is concerned with how the researchers and participants perceive the matter(s) under investigation, and the stance that they have with regard to the interventions being made and their belief in the results (Hughes and Sharrock, 2016). A research philosophy can be defined as the collection of beliefs, philosophies or assumptions about certain phenomena of the world, or their nature and knowledge development about them (Collis and Hussey, 2014). Therefore, this section presents a description of the researcher’s philosophical stance for this study when selecting the adopted method.

Once philosophical issues have been considered, and reflection on the various approaches that could be utilised in their studies, researchers may then decide the most appropriate processes for data collection and analysis. There are three reasons why it is significant to explore philosophy with reference, in particular, to the methodology for research (Easterby-Smith et al., 2018). Firstly, in exploring the research philosophy, a researcher is helped in specifying and refining research methods for utilisation within a research project, while it assists in clarifying the overall strategy to be used. Such reflections impact on the kind of evidence to be gathered, where it comes from and how it will be interpreted, as well as how the research question(s) will be answered. Secondly, knowledge of the research philosophy facilitates the researcher in their evaluation of various methodologies during the early phases, and the identification of limitations to particular approaches helps in avoiding unnecessary work. Thirdly, exploring the research philosophy helps researchers to be creative and innovative in their selection and adaption of methods previously outside their experience. Research methods may be described, categorised and examined at various levels, with the philosophical level having a focus on assumptions in relation to world features at their most general, involving aspects such as reason, matter, the mind and proof of knowledge (Creswell and Plano Clark, 2018). Philosophical aspects underpin methods and facilitate the classification of methods of research into paradigms (Creswell and Plano Clark, 2018). A most pronounced feature of current social research is the concurrent operation of a range of perspectives. Research in the social sciences has many different schools of thought, each of which brings its own adherents, theory-based assumptions and methodological approaches (Jason and Glenwick, 2016). A research philosophy has assumptions with regard to how the world is viewed by the researcher, such as the ontology and epistemology (Saunders et al., 2019); the assumptions made underpin the strategy and methods of a research project (Saunders et al., 2019). Furthermore, researchers ought to clearly understand the assumptions involved as they serve to guide decisions made over the design of all the subsequent research stages (Creswell and Creswell, 2017). Within the next sections, a discussion is presented of the various dimensions to the philosophical assumptions of research, with exploration of the principles behind them.

4.2.1 Ontology

Ontology has regard for the nature of existence and reality, whilst epistemology is related to the ways in which enquiries are made about world nature and phenomena (Easterby-Smith et al., 2018). In accordance with Bracken (2010), ontology presents an image for reality through which theory can be based; alternatively, it can be considered the study of reality through conceptualisation of the very essence underpinning the specific phenomenon or domain under investigation (Holden and Lynch, 2004). The approach has a focus on issues in relation to the state of being a human in a particular world and whether an individual sees social world aspects or social reality as being i) independent, external, pre-given and real in objective terms; or ii) subjectively experienced, socially constructed and resulting from human thoughts that are expressed via language (Usher, 2002). An ontological approach assists methodologies in addressing the nature of reality and what it is that socially-oriented research, indeed, ought to be investigating (Klakegg, 2016). An understanding of those phenomena, therefore, depends on the adopted ontological positions that exist in a continuum from objectivism to constructivism (subjectivism) (Bracken 2010; Bell et al., 2018).

4.2.1.1 Objectivism

Objectivism has been described by Bell et al. (2018) as having a basis in the acceptance that social phenomena and associated meanings exist with a reliance on social actors. There is a belief within objectivist epistemology that objective truths lie waiting for discovery by researchers (Crotty, 1998). As pointed out by Burrell and Mahoney (1992), a position that is objectivist involves the application of models and methods derived from the natural sciences to study of the affairs of people. Objectivists treat the natural world and the social world as if they were one and the same Bell et al. (2018). An objectivist philosophy is considered as being an aspect of positivism (Crotty, 1998).

4.2.1.2 Subjectivism

The subjectivist philosophy is an ontological position asserting that the phenomena of the social world, and their associated meanings, are carried out through social actors and their interactions, are constantly being revised and that they present to us as external facts beyond our influence or reach (Creswell and Creswell, 2017; Bell et al. 2018). Social science researchers have acknowledged this position for the achievement of a holistic understanding of a social situation rather than a reductionist one (Leslie and Caldwell, 2016). Subjectivism rejects the objectivist perspective on human knowledge and, instead, has the belief that there are no objective truths that researchers can discover (i.e. truth or meaning are constructed rather than discovered) (Crotty, 1998). Furthermore, there is an association of subjectivism with constructionism, with the implication that any particular social phenomenon is generated by way of social interaction, and is in a state of continual revision (Bell et al., 2018).

4.2.2 Epistemology

Epistemology may be defined as knowledge theory informing the processes of research (Roots, 2007). Phillimore and Goodson (2004), however, make a distinction between ontology and epistemology. For them, ontology has distinct views of the world that lead towards interesting epistemological problems as there is the implication of differing foundations of knowledge in relation to the social world. The theory of knowledge (epistemology) deals with questions related to truth, namely, what is accepted as being true and the manner in which that is constructed (Bell et al., 2018; Creswell and Creswell, 2017). With such a basis, the conceptualisation of reality has its derivation from processes used for gathering and organising observed symbols and signs. There is an inextricable link between epistemology and the process of research, wherein a researcher explicitly or implicitly adopts knowledge theory (Leslie and Caldwell, 2016). With epistemology, there is a focus on the process of knowledge gathering with the aim of developing new theoretical models (Creswell and Creswell, 2017). Potential connections are provided between formal knowledge theories and the practice of research because, as noted by Leslie and Caldwell (2016), there is an influence on the choice of methodology; the relationships between the participants and the researcher; the manner in which the method quality is demonstrated; and the representation, voice and form within the method. Therefore, there is difficulty in engaging in the creation of knowledge without a tacit assumption, at least, of the epistemological positions taken (i.e. assumptions related to what knowledge is and how it should be constructed) (Tracy, 2019). It should be noted, however, that questions related to epistemology do not get answered through empirical inquiry, since such questions require debate and philosophical argument, wherein there is a concern for the very presuppositions related to knowledge itself (Bell et al., 2018). There are numerous schools of thought related to epistemology in terms of how reality is interpreted, namely, whether it is dynamic, fixed or existing on a kind of continuum with the determination of claims either rationally through reason or through observation of the deconstruction and construction of phenomena (Carter and Little, 2007; Creswell and Plano Clark, 2018). The schools of thought include realism, positivism, pragmatism, advocacy, critical theory, interpretivism (naturalistic inquiry or social constructivism) and postmodernism (Bell et al., 2018; Creswell and Creswell, 2017; Easterby-Smith et al., 2018; Saunders et al., 2019). Those epistemological positions have qualities that impact on the methodology in different ways which, in turn, has a bearing on the research and the approximation of results for any particular setting (Collis and Hussey, 2014; Creswell and Creswell, 2017). Three primary epistemological positions are identified by Bell et al. (2018)—positivism, interpretivism and realism—each of which are discussed below.

4.2.2.1 Positivism

Positivism supports the belief that there is an objective reality that is independent from the researcher (Collis and Hussey, 2014). Caldwell (2015) states that positivism is a kind of epistemology that looks for explanations and the predictions of occurrences within the social world through a search for regularities and any causal relationships that exist between constituent elements. The researcher, however, ought to have objectivity and not be influenced by sources that are non-scientific. A key principle of positivism is that social worlds exist in an external manner (Easterby-Smith et al., 2018); as such, only phenomena that are observable and measurable ought to be accepted in research through methods that are objective (Holden and Lynch, 2004; Leslie and Caldwell, 2016). A positivist paradigm is founded upon the testing of theories to provide explanation, prediction and understanding of social phenomena through empirical research, namely, experiment and observation (Bell et al., 2018; Bryman, 2016; Cooper and Schindler, 2014; Creswell and Creswell, 2017). Indeed, only phenomena that are observable and measurable ought to be accepted in such research, with objective methods seeking ‘facts’ (Sekaran and Bougie, 2016). Moreover, it is assumed that the development of statistical measures for observation and the study of individual behaviour is of overriding importance in positivist research (Bell et al., 2018). A positivist researcher reflects on the need for the examination of causes that impact on outcomes, such as the identification of problems examined within experiments (Creswell and Creswell, 2017). Positivism may be seen as the application of scientific methods to resolve IS problems (Choy, 2014; Mumford et al., 1985; Pickard, 2013), and from this perspective meaningful statements are proposed as being those that may, theoretically at least, have verification (Lazar et al., 2017). With positivism, a high value is placed on the replication principle, in reference to the replication that happens when studies are undertaken through the use of study repetition and the acquisition of findings or results that are similar or identical (Bryman, 2016). Positivists, therefore, place emphasis on replication for the fundamental testing of knowledge, since there is a belief that if identical research is undertaken under the same limitations and conditions, with the use of clear factual data, then the acquired results will have similarity if there is the careful specification of the methods, as well as precise measurement and adherence to standards and facts (Bell et al., 2018; Collis and Hussey, Mumford et al., 1985). Hussey and Hussey (1997) and Creswell and Creswell (2017) note that positivistic approaches involve a process of deduction and explanatory study that entails the investigation of facts or the causes behind social phenomena. A paradigm that is positivist, however, involves methods that are quantitative, the analysis of statistics and surveys, and empiricist research (Bryman, 2016; Choy, 2014; Collis and Hussey, 2014; Cooper and Schindler, 2014; Sekaran and Bougie, 2016). With a positivist philosophy, there is an assumption that the analysis must be expressed in a form that can be generalised (Bell et al., 2018). Thus, the data ought to be gathered from samples that are sufficiently large so that there is representativeness and the findings will be generalisable (Creswell and Creswell, 2017).

4.2.2.2 Interpretivism

The philosophical stance of interpretivism reflects a position that is entirely different or opposing the epistemological stance of positivism. Bell et al. (2018) argue that knowledge development from the interpretivist perspective may only be acquired through an understanding of the differences that exist between human social actors based on their differing viewpoints in relation to the world; this contends with the position of the positivist that a researcher may study phenomena independently from the research subjects (the ontology of objectivism) and undertake research in a way that is value free (Bell et al., 2018). Creswell and Creswell (2017) claim that interpretivism was developed because of criticism and the perceived insufficiencies in the positivist paradigm. From the interpretivist standpoint, social reality does not have objectivity, but rather is shaped by the perceptions of people and thus can be considered as highly subjective (Creswell and Creswell, 2017). As Collis and Hussey (2014) note, with an interpretivist philosophical position, a great deal of value is attached to the empathetic stance of the researcher, which enables their entry into the social milieu of the study participants with an understanding of the meaning they attach to phenomena (the ontology of subjectivism). An interpretivist philosophy serves to underpin a process that is inductive, since it aims at building theory (Gill and Johnson, 2010). As an interpretivist philosophy encourages researchers to immerse themselves in the matter under study, wherein the values and interpretations of the researcher may not be detached from the study, it entails an axiological stance that can be considered as being value laden. Creswell and Creswell (2017) suggest that researchers working through the prism of the interpretivist philosophy have a tendency to employ an inductive approach in order to understand the phenomenon being scrutinised from the perceptual lenses of the study participants. There is application of an interpretivist philosophy within most qualitative strategies, which can be considered as subjective (Bryman, 2016; Choy, 2014; Collis and Hussey, 2014; Cooper and Schindler, 2014; Sekaran and Bougie, 2016). Therefore, data ought to be collected from small samples, and by means of unstructured in-depth interviews, textual analysis, ethnographic case studies and focus groups (Jonker and Pennink, 2014). With this paradigm, generalisability is not important since studies have the aim of acquiring a deep understanding of the structures of the phenomena (Bell et al., 2018; Creswell and Creswell, 2017; Quinlan et al., 2018).

4.2.2.3 Realism

Within realism, there is an assumption that a ‘real world’ exists that is ready to discover despite, perhaps, it being apprehensible only imperfectly (Amolo et al., 2018). Realism aligns with positivist approaches in two facets: there is a belief that the social and natural sciences are able to adopt identical approaches for the collection of data and provision of explanation, and there is a view that there is an external reality that exists independently from any descriptions that we may have of it (Bell et al., 2018). There are two kinds of realism: critical realism, where the observations and experiences are images of the world; and empirical realism, where what is seen is considered to be a direct experience of what it is (Bell et al., 2018). For McEvoy and Richards (2006), aspects of phenomena that may not be conveyable through senses have to undergo forms of social conditioning, through which interpretations of reality occur. McEvoy and Richards (2006) also suggest that despite this philosophy seemingly adopting an ontological position that is objectivist, there is room for researchers to acquire an understanding of phenomena through various interpretations of the involved social actors (the ontology of subjectivism). The work of Håkansson (2013) aligns with that of McEvoy and Richards (2006) in suggesting that critical realist approaches value the mental processes, by which there may be representation of the truth, with Håkansson (2013) arguing that researchers working realism should understand the underlying social structures related to phenomena so that a true picture can be apprehended.

- **Justification for the philosophy adopted by the research**

Within this study, the philosophy behind the project is best described as an ontology of objectivism and an epistemology of positivism. As discussed, positivist approaches are employed in addressing problems requiring the assessment of causes having a bearing on outcomes. For this research, the primary cause is considered to be the impact that implementation factors of BI have on the success of BI. In light of the various models and theories related to the topic of success in BI implementation, a hypotheses-based framework was developed for this study. Bearing in mind there is an end goal of the testing and validation of the research hypotheses via the framework proposed the study has a focus on causality which, in itself, is linked to the positivist philosophy. Moreover, this research focuses on the objective testing of the primary constructs of both the dependent variables for BI success, and the independent variables relating to the implementation factors for BI. The achievement of such testing is more likely to occur through the adoption of an ontology of objectivism, with the assumption that the study is undertaken in a value-free manner, with an independent researcher maintaining an objective position.

Within IS research, there has been extensive debate between academics with regard to which kind of approach to research is most appropriate to employ. Some have expressed a preference for an interpretive philosophy (Arnott, 2008; Pham et al., 2016), whilst others have argued that a positivist philosophy is more appropriate (Hatta et al., 2017; Choy, 2014; Mumford et al., 1985; Pickard, 2013; Woodside, 2011). Within this research, the approach accords to a positivist philosophy instead of an interpretive one for a number of reasons. Firstly, after an extensive examination of studies related to the field, research hypotheses were planned for this study that could be checked through the collection of data through a self-completed questionnaire. As such, there remains a detachment of the researcher from the problem realm (Bryman, 2016). Secondly, with a positivist philosophy, there is often an emphasis on existing theories being the knowledge sources of most importance (Collis and Hussey, 2014; Cooper and Schindler, 2014; Creswell and Creswell, 2017). In fact, in general, positivist research tends to be established based on relationships that have been previously examined (Bell et al., 2018). Furthermore, there is the retention of neutrality throughout the entire process of such a research project. Lastly, the positivist philosophy fits for this research as it allows for a theoretical focus that is clear and facilitates the gathering of numerical data which, when collected, can be compared easily (Easterby-Smith et al., 2018).

4.3 Research approach

The research approach chosen is significant as it allows the researcher to engage in informed decision-making with regard to the research design, while helping in terms of the selection of the strategic fit most appropriate for the study. Moreover, the imposition of constraints helps the research design to suitably adapt (Easterby-Smith et al., 2018). Induction and deduction are the two main research approaches (Creswell and Creswell, 2017), which outline the nature of the intended relationship between the research and theory (Bell et al., 2018; Collis and Hussey, 2014; Sekaran and Bougie, 2016). An inductive approach is primarily associated with the use of qualitative methods, whilst a deductive approach is mainly associated with methods that are quantitative. As noted by Creswell and Creswell (2017), with a deductive approach, a researcher begins with the development of theory and then prepares hypotheses. Following this, data are collected, analysed and the hypotheses are finally either accepted or rejected, which places the researcher in the possession of empirical evidence in relation to particular phenomenon. With an inductive approach, on the other hand, the researcher begins with observations of a phenomenon that are then analysed for emerging themes and patterns. Following this, relationships are identified and theory is developed based on the research undertaken (Creswell and Creswell, 2017).

4.3.1 Deductive

A deductive approach helps the researcher to create a research strategy for testing hypotheses and then draw conclusions through logical reasoning (Bell et al., 2018; Collis and Hussey, 2014; Sekaran and Bougie, 2016). With a deductive approach, the researcher begins with theory and ends with the determination of the research results; the research is, in essence, guided by theory (Creswell and Creswell, 2017). Beginning with theory grounded in existing research, researchers seek to find solutions to existing problems. Then, hypotheses are developed based on the existing theory, which is examined via the consideration of the empirical observations made. After that, the collected data are examined to acquire the study results and, at a later point, the proposed hypotheses based on the research findings are either rejected or accepted. Lastly, if necessary, adjustments are made to the theory (Bell et al., 2018; Collis and Hussey, 2014; Easterby-Smith et al., 2018).

4.3.2 Inductive

The inductive approach is the opposite of its deductive counterpart since inductive research involves the development of theory from observations made from empirical reality (Creswell and Creswell, 2017). With induction, the research outcome is theory (Bell et al., 2018; Sekaran and Bougie, 2016). Inductive processes involve the drawing of conclusions that are generalisable from particular observations (Creswell and Creswell, 2017). The inductive approach lends itself to the development of an appreciation of how people interpret their social milieu (Collis and Hussey, 2014). The approach moves from observations to conclusions (Cooper and Schindler, 2014), whereby the researcher begins with particular measures and observations, seeks regularities and patterns from which tentative hypotheses can be formulated that can be investigated later, and finally generates general theories from the conclusions (Gill and Johnson, 2010).

- **Justification for the research approach**

Creswell and Creswell, (2017) suggests that there are three criteria in practice for selecting the approach to research: i) the research topic nature, ii) the time available to the researcher, and iii) the degree to which the researcher is willing to take on risk. The main objective of this research is to determine the effects of implementation factors for BI on BI success. As such, a deductive approach is adopted for the study, within which there is the development and testing of a theoretical framework through empirical data. The survey method will be employed in the collection of primary data hailing from a particular sample population. Then, the collected data will be statistically analysed, with the aim of generalising the results to the wider population (Bell et al., 2018).

4.4 Research strategy

The term 'research strategy' refers to the general orientation for conducting the research project (Bell et al., 2018). A research strategy is the orderly and systematic way in which data are collected and analysed in order to acquire information to answer the research questions posed (Pickard, 2013). Furthermore, the strategy entails the relationship, in methodological terms, between the methods of data collection and analysis (Sekaran and Bougie, 2016). The methods can be defined as the particular procedures and techniques used in the collection and analysis of data (Cooper and Schindler, 2014). For Carter and Little (2007), the strategy provides the overall research direction, including the processes through which the research is undertaken. Collis and Hussey (2014) note that all research strategies have their own approaches for empirical data collection and analysis. As such, the selection of a strategy that is suitable for the particular phenomenon or research problem(s) is, therefore, critical. Qualitative, quantitative or mixed-method approaches are the primary research strategies used for the collection and analysis of data within social science and management research Bell et al., 2018; Creswell and Creswell, 2017; Gill and Johnson, 2010; Bernard, 2013).

4.4.1 Quantitative research strategy

A quantitative research strategy refers to the employment of computational and/or mathematical (statistical) techniques for the investigation of social phenomena in an empirical manner through the development and employment of theory, mathematical models and/or hypotheses in related to the phenomena being studied (Bell et al., 2018). Furthermore, quantitative research within business and management area is defined by Cooper and Schindler (2014) as the choice of statistical methods, linked to social strategy, that deliver a picture of how society has been changing. Therefore, the primary objective for quantitative studies is data quantification that enables generalisations to be made from the results obtained from the research sample to the entire population concerned (Creswell and Creswell, 2017). Quantitative studies are regularly linked to positivism (Collis and Hussey, 2014). They employ the logic of deduction from the natural sciences, and are generally undertaken for the purposes of explanation (Bell et al., 2018; Creswell and Creswell, 2017; Sekaran and Bougie, 2016). Within quantitative research, numbers are used by the researcher for description (Cooper and Schindler, 2014). Two key approaches involved in quantitative research are surveys and experiments (Creswell and Creswell, 2017). A survey is the research strategy that is most commonly adopted within research in management and business (Bryman, 2016). In general, the survey is employed in gathering data from a research sample with the aim of statistical analysis of the data and the generalisation of the findings to a wider population (Bell et al., 2018). The techniques often associated with the collection of quantitative data include structured interviews and questionnaires that have fixed answers with subsequent statistical data analysis (Bell et al., 2018; Collis and Hussey, 2014). Usually, quantitative data relates to a small volume of information gathered from a large sample (Creswell and Creswell, 2017), where the aim is the elimination of possible bias sources with the intention of generalisation from the research sample to a broader population (Easterby-Smith et al., 2018).

4.4.2 Qualitative research strategy

Qualitative research can be considered as seeking to understand human behaviours and the reasons/causes behind them; the bases for the findings are broad questioning, data collection from various sources and the reporting of the information analysed (Creswell and Creswell, 2017). Qualitative research is an approach that is unstructured, whereby there is flexibility in the processes, design and objectives of the research, as well as the questions and sampling (Cooper and Schindler, 2014). The philosophy that underpins qualitative research is empiricism (Cooper and Schindler, 2014). Qualitative research is undertaken to describe, understand and explain social situations, phenomena, individuals or the circumstances that surround phenomena in the form of the written word (Bell et al., 2018). Qualitative research offers the opportunity to acquire a deeper understanding of people, as well as the social and cultural issues that surround the research (Creswell and Creswell, 2017). Therefore, qualitative research is primarily exploratory rather than confirmatory in nature (Bernard, 2013), with the outcomes of a qualitative approach not reached through statistical procedures or other quantification means (Quinlan et al., 2018), but rather through a heavy reliance on the words acquired from a relatively small participant sample (Bell et al., 2018). As opposed to positivism, qualitative research is known for its relevance to an interpretivist philosophy (Collis and Hussey, 2014). Moreover, it relates to inductive approaches where the study result is new theory (Bell et al., 2018; Sekaran and Bougie, 2016). Usually, the approaches applied within a qualitative research strategy are grounded theory, phenomenology, ethnography, case studies and so on, through the use of techniques such as questionnaires, observation, document analysis, participation and interviews (Bell et al., 2018; Creswell and Creswell, 2017; Cooper and Schindler, 2014). Qualitative research has the aim of obtaining in-depth detail rather than generalised statistical information (Creswell and Creswell, 2017), with this kind of research suitable for deductive studies since the purpose is the generation of hypotheses rather than the testing of theory (Collis and Hussey, 2014).

4.4.3 Mixed-method strategy of research

Mixed-method research is the third kind of strategy, wherein researchers frequently incorporate the use of both qualitative and quantitative techniques within various designs, such as the sequential mixed-methods type, the sequential multi-phase type and the concurrent mixed-methods type of design (Creswell and Creswell, 2017; Cooper and Schindler, 2014). Furthermore, a mixed-method research design could include both inductive and deductive approaches for the development of theory; the approach nature, then, could be confirmatory and exploratory (Pickard, 2013). Creswell and Plano Clark (2018) note that significant benefits could be accrued from the employment of mixed methods within a single study. Firstly, there be can the application of different methods within a study for different purposes. Secondly, triangulation may be used within mixed-method research, that is, the use and combination of various theoretical perspectives in one research project, as well as different methodologies and methods, along with various techniques and multiple data sources. Thus, triangulation helps to reduce or remove the bias that frequently occurs when using one single approach, since it permits the forming of better assessments for the general explanation for phenomena, while increasing the results' reliability and validity (Bell et al., 2018; Creswell and Plano Clark, 2018).

- **Justification for the research strategy**

The selection process related to choosing a suitable strategy for research is based on several factors such as the research nature, the problem being addressed, the kind of data needed and the degree of accessibility of that data (Punch, 2005). This study project can be categorised as having a quantitative research strategy with a positivist and deductive philosophy. The study follows a scientific study process, wherein causal relationships may be established that exist between various variables. Suitable achievement of the study aims will be achieved through analysis of the quantitative data, enabling the formulation and understanding of relationships, and thus the impacts that variables have within the proposed framework. Since there statement and testing of the hypotheses in functioning form, one outcome is that the author could infer a central meaning to relationships between the implementation factors of BI and BI success, as well as the direction and strength of those relationships. Furthermore, quantitative procedures are believed to serve an essential role in the measurement of behavioural and physiological elements such as opinions, emotions and attitudes, which are a primary consequence of this investigation (Bell et al., 2018). As such, research of a quantitative type, through the use of a questionnaire survey, is considered the most appropriate strategy for this study.

4.5 Research design

The term 'research design' refers to the plans and procedures required to enable the fulfilment of the research objectives and to answer the research question(s) posed at the start of the project (Easterby-Smith et al., 2018; Saunders et al., 2019). Careful design of the research helps in establishing the research limits and reducing the risk of drawing inaccurate conclusions from the data collected with regard to the causal effects (Creswell and Creswell, 2017). Jason and Glenwick (2016) describe research design as the art and science of planning the procedures to be undertaken in studies in order to maximise the value and validity of the findings, while Jason and Glenwick (2016) define it as the plan for the examination and provision of answers to the research question(s). For this study project, the design of the research consists of the particular objectives that emerged from the overall research, the methods of data collection and analysis, and any ethical considerations (Bell et al., 2018). Key aspects of the research design are explained within the sections that follow, with Figure 4.1 providing a visual overview of the study's research design. There are four key types of design that research may be classified into, according to the study's purpose: i) exploratory, ii) descriptive, iii) explanatory or casual, and iv) some combination of i–iii (Bell et al., 2018; Creswell and Creswell, 2017; Collis and Hussey, 2014; Sekaran and Bougie, 2016). As noted by Newbold et al. (2013), descriptive research has a focus on questions of a 'who', 'what' and 'where' nature, whereas explanatory research focuses on 'why' and 'how' questions, and exploratory research places its focus on questions of a 'what' nature. Descriptive research is conducted with the purpose of producing accurate representations of situations, events or people (Bell et al., 2018); explanatory research studies situations so that an explanation can be provided for the causal relationships amongst the variables that exist in the study object (Creswell and Creswell, 2017); while exploratory research seeks new insights with regard to phenomena, and calls for more detailed descriptive levels with regard to the study object, and involves the asking of questions and the assessment of phenomena that reflects on the matter under investigation in fresh ways (Cooper and Schindler, 2014). Explanatory research will be employed within this study to provide an overview of the research problem through a review of the literature, the development of a conceptual framework and associated hypotheses. The design will facilitate in further identifying relationships between the study variables. The study design process, as shown in Figure 4.1, began with the selection of the topic or area of interest. Then, a critical and comprehensive literature review was undertaken in order to identify gaps within the existent literature, to help clarify the reasons for undertaking the research, and to extend knowledge with regard to the successful implementation of BI. Accordingly, following the identification of the research problem, the research framework is developed and the justification for the study elaborated, based on the literature. Next, the approach and strategy of the research is selected based on the study objective. After that, the primary data are collected through the survey strategy, followed by the data analysis through an analytical tool set. Then, a deep discussion is carried out with regard to the results obtained. Finally, within the conclusion, a summary of the study and its limitations can be found, as well as the provision of recommendations and suggested areas for future research.

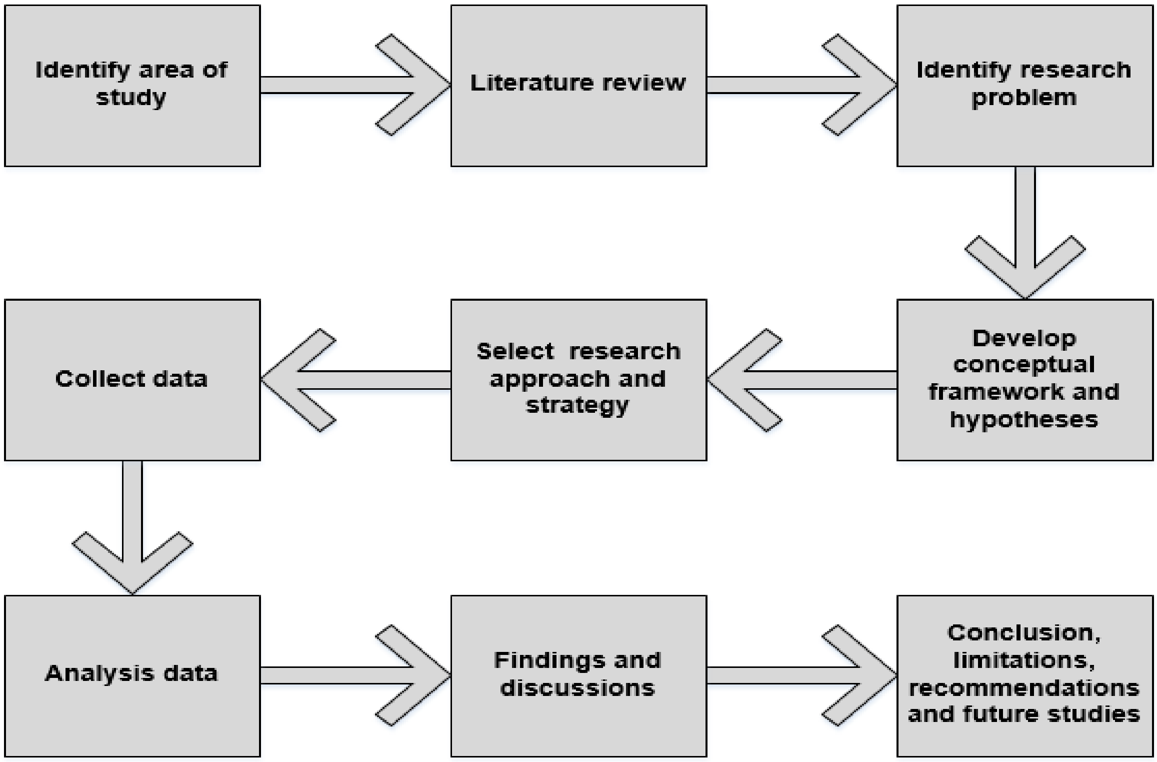

Figure 4.1 Research design
(Source: the author)

4.6 Data collection method

There are many research methods available for the collection of data such as interviews, questionnaires, focus groups and observations, which can be classified as being either qualitative or quantitative (Bell et al., 2018; Creswell and Creswell, 2017; Easterby-Smith et al., 2018; Gill and Johnson, 2010). The selection of a suitable method for data collection depends on various factors such as the research timeframe, the resources available to the researcher(s), the degree of accuracy expected for the study, the level of expertise of the researcher(s), and the costs associated with each particular method. For Sekaran and Bougie (2016), a quantitative method can be considered as one where numerical data are either used or generated by a procedure for data analysis (e.g. through statistics or graphs) or a data collection technique such as a survey using a questionnaire. As discussed above, a questionnaire survey will be employed as the main data collection technique for this study. The survey is defined by Creswell and Creswell (2017) as an instrument to gather a numerical or quantitative description of opinions, attitudes or trends within a population through the study of a smaller sample of the wider population. A major advantage of the questionnaire survey is the ability to collect data from a large research sample in a way that is accurate, efficient and very economical (Bell et al., 2018; Collis and Hussey, 2014; Crotty, 1998). Data from questionnaires are standardised and can be administered and compared easily. In general, questionnaires provide data that are highly reliable and valid (Bell et al., 2018). Most survey questionnaire results have representativeness for the entire population, and thus there is the capacity to generalise from a sample to the population as a whole (Creswell and Creswell, 2017). Two key types of questionnaire survey are the self-completion type and those using structured interviews (Bell et al., 2018). With a self-completion questionnaire, respondents complete the questionnaire independently (Bell et al., 2018), while in surveys that involve structured interviews, the participant’s responses are recorded by the interviewer (Crotty, 1998). Surveys with structured interviews may involve telephone surveys and structured interviews, whereas questionnaire surveys carried out through self-completion may involve postal, internet, mediated intranet and delivery-for-later-collection mediums (Bell et al., 2018; Creswell and Creswell, 2017; Collis and Hussey, 2014; Crotty, 1998). Within this research project, the web-based self-completed survey questionnaire was selected and considered appropriate for the collection of the data required. The questionnaire was distributed online to a sample selected through the General Trade Union of Workers in Mining and Metal Industries for Jordan. E-mail was used by the researcher to send two links to two questionnaire versions available online for data collection, one in Arabic, and the other in English. This research utilised the self-completion style of questionnaire as the costs are lower, administration time quicker, and there will be less bias. Moreover, the technique offers the opportunity to including visual images and enable access to respondents that could not be contacted by telephone (Bell et al., 2018; Creswell and Creswell, 2017; Crotty, 1998). Furthermore, within recent years, there has been an increase in popularity of web-based self-completion questionnaire surveys, which are perceived as being quick and easy to distribute and deliver, are facilitative of faster responses, require fewer resources, and enable good quality data to be gathered at lower cost with less time spent on data entry and more options available for the design (Creswell and Creswell, 2017; Cooper and Schindler, 2014; Sekaran and Bougie, 2016).

4.6.1 Questionnaire design

The questionnaire design affects the rate of response, as well as the reliability and the validity of the data (Collis and Hussey, 2014). To obtain a high rate of response and to reduce non-response bias, there is a need to construct and design questionnaires that are clear and effective through ensuring an appropriate appearance and clear instructions (Bell et al., 2018). McEvoy and Richards,(2006), Collis and Hussey (2014), Sekaran and Bougie (2016), Creswell and Creswell (2017) and Bell et al. (2018) all highlight that key aspects must be given consideration when designing questionnaires. An initial aspect is to ensure that each of the individual questions has been designed carefully. There is a need to identify the information needed and choose the content of the questions through determination of their format and type, and the kind of response desired. Then, having decided on the wording of questions, the flow of the questionnaire needs to be established with a clear layout, while an accompanying cover letter is required with a clear explanation of the questionnaire purpose. After that, a pilot test must be conducted and, following any refinement, the final questionnaire version can be produced. Finally, the administration of the questionnaire can commence.

In developing the questionnaire survey, naturally, it was kept in mind that the issues of IS and success in the implementation of BI had been explored previously by other researchers. As such, and in accordance with advice from the work of scholars such as Sekaran and Bougie (2016) and Creswell and Creswell (2017), the decision was made that the development of a new instrument was not necessary as other questionnaires had been developed that were suitable for this kind of research and had proven their capacity to acquire the detailed information required. When the design considerations for the questionnaire were complete, as founded on the conceptual framework proposed within Chapter 3, the study questionnaire was adapted to the various measures and items previously validated in the literature. There was validation of the items adapted, and semantic changes were carried out to ensure compatibility with the instrument. As Creswell and Creswell (2017) notes, borrowing constructs that have been measured within previous studies leads to a much easier, faster and ultimately superior process. Furthermore, since the questionnaire was originally developed in the English language, there was a need to translate it into Arabic, since that is the primary language used within Jordan, this translation was completed by a certified translator (see Appendix 2). Academic staff (PhD holder) based in Mutah University in the Department of Management Information Systems, with knowledge of management information system and the design of a questionnaire for IS and BI, undertook a review and assessment of the Arabic and English versions to ensure they were valid and appropriate.

A questionnaire can have two kinds of question: closed-ended or open-ended (Cooper and Schindler, 2014). The questionnaire in this research project used questions that were closed-ended as: i) they are suitable for large surveys (Bell et al., 2018); ii) answers hailing from questions that are closed-ended may be directly transferred into a computerised database, since it is much easier for them to be tabulated and coded, before analysis within a computer system; and iii) closed-ended questions have a greater flexibility and facilitate in the acquisition of more sensitive information than open-ended questions (Creswell and Plano Clark, 2018; Easterby-Smith et al., 2018; Gill and Johnson, 2010). The items of measurement adapted within this research are closed-ended questions to ensure the measurements are both consistent and valid (see Table 4.1). The scales employed within this research are ordinal and nominal. The ordinal scales were utilised the determine the work level, qualifications, and so forth, whilst the nominal scales were limited to questions with regard to the demographic characteristics of the respondents such as gender. Furthermore, the Likert scale was used for statements investigating the opinions and beliefs of the participants in regard to evaluation of the effectiveness of training (Bell et al., 2018). The 5-point Likert scale was employed in this study (where 5 = strongly agree, 4 = agree, 3 = neutral, 2 = disagree, and 1 = strongly disagree). Hair et al. (2018) consider that increases to the scale point number may have the benefit of a reduction in rounding error; however, it can also increase the costs of administration, lead to respondent fatigue and non-responsive bias. Furthermore, Newbold et al. (2013) recommend that researchers use the 5-point Likert scale rather than the 7-point scale, particularly when undertaking attitudinal research. The developed questionnaire concentrated on the achievement of a logical idea sequence to assist the respondents in their completion (see Table 4.1 and Appendix 3). The approach resulted in a format with three parts, with progression from a general information section to one regarding factors in regard to the implementation of BI, and finally the measures of success for the implementation of BI. The respondents could navigate forwards and backwards through the pages of the survey and, if they wished, change their responses. All of the instructions needed for the respondents to complete the survey were included on each questionnaire page.

More specifically, the questionnaire instructions were as follows:

Part A*: *General background information. Part A is composed of 7 questions to gather general demographic information, the profile of the company and details with regard to the implementation of BI in the company.

Part B*: *Implementation factors. Part B is composed of 47 items for determination of the factors that respondents believe have an effect on BI implementation success.

Part C*: *Measures of success for the implementation of BI. Part C is composed of 19 items for the measurement of success in the implementation of BI.

Table 4-1 The survey items adapted

Construct	Item code	Questionnaire statement	Source
Business plan and vision (BPV)	**BPV1**	The business plan and vision align with the company's mission, goals, objectives, and strategies	Raghunathan (1992), Kearns and Sabherwal (2006)
	BPV2	The business plan and vision contain quantified goals and objectives	
	BPV3	The business plan and vision contain detailed action plans/strategies that support the company direction	
	BPV4	The business plan and vision activities are instrumental in providing cross-functional integration	
	BPV5	The business plan and vision contribute to the success of the company and the business intelligence system	
Management Support (MS)	**MS1**	Overall, management has encouraged the use of a business intelligence system	Igbaria et al. (1997), Klein et al. (2001), Wixom and Watson (2001)
	MS2	User satisfaction has been a major concern of management	
	MS3	Management is strongly committed to the successful implementation of business intelligence	
	MS4	Management takes an active interest in business intelligence problems and successes	
	MS5	Management provides necessary resources for business intelligence implementation	
Champion (CH)	**CH1**	The project champion is willing to listen to implementation problems	Lim et al. (2000), Kayworth and Leidner (2001), Wixom and Watson (2001)
	CH2	The project champion encourages people to work as a team	
	CH3	The project champion is primarily concerned with getting the job done	
	CH4	The project champion encourages participative decision-making	
	CH5	The project champion comes from the information system domain	
Resources (R)	**R1**	The business intelligence project was adequately funded	Wixom and Watson (2001)
	R2	The business intelligence project had enough team members to get the work done	
	R3	The business intelligence project was given enough time for completion	
Project Management (PM)	**PM1**	Project management success in assessing the project performance in the early stages of implementation	Grover et al. (1995)
	PM2	Project management success in measuring implementation performance	
	PM3	Project management success in gaining control of business intelligence implementation	
	PM4	Project management success in communicating between business intelligence	

		implementation team members and other company members	
Team Skills (TS)	**TS1**	The members of the project team were from different areas of expertise	Wixom and Watson (2001), Lee and Xia (2010)
	TS2	The members of the project team (including consultants) had the right technical skills for business intelligence	
	TS3	The members of the project team had good interpersonal skills	
	TS4	The members of the project team had skills that complemented each other	
	TS5	The members of the project team had a variety of different experiences	
	TS6	The members of the project team varied in functional backgrounds	
Change Management (CHM)	**CHM1**	The change management support was available whenever I needed it	Venkatesh et al. (2011)
	CHM2	The change management consultants understood my problems well	
	CHM3	The change management consultants resolved the problems I faced	
Data Source System (DSS)	**DSS1**	Common definitions for key data items were implemented across the source system	Wixom and Watson (2001)
	DSS2	The data sources used for business intelligence were diverse and disparate applications/systems	
	DSS3	A significant number of source systems had to be modified to provide data for business intelligence	
Information Technology Infrastructure (ITI)	**ITI1**	Appropriate hardware, software, and network infrastructure were in place prior to business intelligence implementation	Karimi et al. (2007)
	ITI2	Necessary server and database technologies were implemented before implementing the business intelligence system	
	ITI3	Necessary hardware and software were installed before the start of this project	
Attitudes Toward Technology (ATT)	**ATT1**	Using a business intelligence system is a good idea	Venkatesh et al. (2003), Kim (2009)
	ATT2	Business intelligence system makes work more interesting	
	ATT3	Working with a business intelligence system is fun	
	ATT4	I like working with a business intelligence system	
Trust (T)	**T1**	I can trust the business intelligence system	Cyr et al. (2009)
	T2	I trust the information presented on the business intelligence system	
	T3	I trust the transaction process on the business intelligence system	
User Participation (UP)	**UP1**	Users actively participate in determining system requirements	Ravichandran and Rai (1999)
	UP2	Users actively participate in identifying input/output needs	

	UP3	Users actively participate in developing test plans	
System Quality (SQ)	**SQ1**	Business intelligence system is reliable (it is always up and running, runs without errors, and does what it is supposed to do)	Barki et al. (2001)
	SQ2	It is easy to tell whether the system is functioning correctly	
	SQ3	Business intelligence system can recover from errors, accidents, and intrusions while maintaining data security and integrity	
	SQ4	Business intelligence system can easily be modified to meet changing user requirements	
	SQ5	Business intelligence system can easily be adapted to a new technical or organisational environment	
	SQ6	Business intelligence system is easy to maintain	
	SQ7	Business intelligence system is easy to understand	
	SQ8	Business intelligence system is easy to use	
	SQ9	Business intelligence system performs its functions quickly	
Information Quality (IQ)	**IQ1**	Business intelligence system provides sufficient information	Teo et al. (2008), Liu and Goodhue (2012)
	IQ2	Through the business intelligence system, I get the information I need in time	
	IQ3	I am satisfied with the accuracy of the business intelligence system	
	IQ4	Information provided by the business intelligence system meets my needs	
	IQ5	Information provided by the business intelligence system is in a useful format	
	IQ6	Information provided by the business intelligence system is clear	
Decision Quality (DQ)	**DQ1**	As a result of the business intelligence system, I am satisfied with the outcomes of this decision	Visinescu et al. (2017)
	DQ2	As a result of the business intelligence system, I believe I made a good decision	
	DQ3	As a result of the business intelligence system, in retrospect, I believe I made the right decision	
	DQ4	As a result of the business intelligence system, the decision that I made resulted in the desired outcome	

4.6.2 Pilot study

A pilot study has the purpose of testing the validity and reliability of the survey instructions and determining whether the acquired data could be analysed as intended (Bryman, 2016). Thus, as Sekaran and Bougie (2016) note, in essence a pilot study provides an examination of whether a proposed questionnaire is feasible through the presentation of it to a few individuals in a small sample who are representative of the intended population, with the same conditions as those anticipated when the proper study is being undertaken. The pilot study has the advantage of helping to reduce the degree and/or amount of problems through measurement of the time and resources needed, the identification of potential points of confusion and any likely issues for the management of data. Bell et al. (2018) assert that it is essential to conduct a pilot study prior to administering the proper questionnaire survey, since it helps in the detection of potential design shortcomings. Similarly, Creswell and Creswell (2017) argue that pilot tests ensure there is clarity, while they increase the measure reliability and potential for replication of the tools employed in the gathering of data. Furthermore, feedback from a pilot study may help in improving a questionnaire to the extent that the data acquired is much more reliable, valid and rich; this may then vastly improve the potential of the research to achieve its aim and objectives (Crotty, 1998). As mentioned above, in respect to participation within a pilot study, only a small participant sample ought to be sought from those hailing from the population being targeted (Gill and Johnson, 2010). Therefore, once the online questionnaire had been reviewed and revised, it was emailed with a suitable clear covering letter (see Appendix 3). The sample selected for this pilot study comprised of 40 decision-makers contacted through the General Trade Union of Workers in Mining and Metal Industries for Jordan, with a request for completion of the questionnaire along with the provision for feedback with regard to its style, content and clarity. The covering letter gave the participants a full briefing as to the survey purpose and its importance. Those involved were assured that the survey was being carried out in confidence, and they were provided with instructions for the completion of the survey and definitions of the terms used.

- **The descriptive statistics used in the pilot study**

This section presents the pilot participants' demographic profiles and any other information of a general nature. Table 4.2 shows the profiles, where it can be seen that there is classification of the respondents according to seven different categories: gender, level of education, age, level of function, level of management, BI implementation level and the software utilised within the implementation of BI. As mentioned above, the survey was distributed online to a pilot study sample of 40 decision-makers via email. Of those 40 questionnaires, eight were incomplete, and so the final sample for the pilot study comprised of 32 individuals. Of those 32, the majority were male (84.4%), while the minority were female (15.6%). In terms of age, the majority of the participants fell into the 41–50 age group (n=17), with only eight participants aged 31–40 years, three aged 21–30 years, and the remainder aged over 50 years (n=4). With regard to the level of education, the vast majority of the respondents (81.3%) held a degree at the Bachelor's level, 9.4% were holders of a Master's degree, and 9.4% held a Diploma-level degree. As can be seen in Table 4.2, the respondents were asked which functional areas they worked in, where mid-level managers made up 56.3% of the sample, with managers at the operational level comprising 43.7%. Therefore, the respondents hailed from various backgrounds. With regards to the level of implementation of BI, there was full implementation of 93.8% of the initiatives for BI, with the remaining 6.3% being only partially implemented. A majority (78.1%) of the respondents' organisations had implemented Microsoft BI, while a customised system of BI had been deployed by 12.5% of the participants, and a further 6.3% had elected to use Oracle BI, with IBM BI being implemented by 3.1% of the participants.

Table 4-2 Descriptive statistics for the pilot study respondents (n=32)

Characteristic	Item	Frequency	Percentage
Gender	Male	27	84.4%
	Female	5	15.6%
Age	21–30	3	9.4%
	31–40	8	25%
	41–50	17	53.1%
	>50	4	12.5%
Education Level	Master	3	9.4%
	Bachelor	26	81.3%
	Diploma	3	9.4%
Functional Area	Business Development	3	9.4%
	Finance	2	6.3%
	Human Resources	3	9.4%
	Information Technology	5	15.6%
	Legal	1	3.1%
	Operations/Manufacturing	10	31.3%
	Marketing	4	12.5%
	Sales	1	3.1%
	Supply Chain	3	9.4%
Managerial Level	Middle Management	18	56.3%
	Operational Management	14	43.8%
Level of Implementation	Fully Implemented	30	93.8%
	Partly Implemented	2	6.3%
Software Used	Microsoft BI	25	78.1%
	Oracle BI	2	6.3%
	IBM BI	1	3.1%
	Custom developed	4	12.5%

- **Measurement evaluation for the pilot study (Validity)**

Any measures that researchers develop have to be tested for their capability to achieve that which the researcher intends. Therefore, there are certain tests for validity that have to be undertaken. Bell et al. (2018) note that the validity type most broadly recognised as needing to be established when undertaking the development of a new measure is content validity. The term ‘content validity’ refers to the extent to which an instrument employed by a researcher seems to be logical or realistic for measuring what is supposed to be measured (Sekaran and Bougie, 2016). As such, the measure ought to reflect the concept content for that being considered (Bell et al., 2018). Within this research, the items in the questionnaire were definitively chosen once there had been a comprehensive review of the literature on BI in relation to perceptions of the implementation of BISs and the theory of success in BI. The review assisted the researcher in identifying specific measures shown as being successful within other studies, and, therefore having good content validity. The logic applies that elements of the instrument that had been previously developed and applied in the literature were already known to have reliability, and so it was only necessary to validate the additional measures. Therefore, two questionnaire versions (one Arabic and one English) of the main survey were reviewed with the help of a number of academic researchers and experts (PhD holder) within the BI field, who were based at Mutah University. The request was made that they check the appropriateness and relevance of the research instrument with regard to its ability to achieve the research aim and objectives. Another review of the questionnaire was carried out to ensure that the respondents were able to understand the questions, where the testing involved several managers from within the Jordanian mining sector who were asked for their feedback with regard to the overall structure of the questionnaire and the way it was phrased. Feedback gleaned from all of the responses showed that the participants were in agreement that the instructions for the questionnaire had clarity, the questions were straightforward, and the layout of the questionnaire was considered attractive.

- **Measurement evaluation for the pilot study (Reliability)**

The term 'reliability' refers to the extent to which measures may be said to have freedom of error or be unbiased, and thus the extent to which they can ensure consistent measurement over time and with various instrument measurements (Sekaran and Bougie, 2016). The first measure that was calculated for assessment of the construct reliability and quality during a pilot study was the alpha coefficient, which as Churchill (1979) and Nunnally and Bernstein (1994) suggest was applied to all measurements. For this study project, Cronbach's measurement of alpha for internal consistency was calculated in order to evaluate the overall reliability of the scale of measurement. The results in Table 4.3 show that all constructs' reliability are accepted. The estimation of the total variance proportion that is not due to error is given by alpha, and thus the score of alpha is an indicator of the scale's reliability (Newbold et al., 2013).

Table 4-3 Reliability test for pilot study (n=32)

Constructs	No. of items	Cronbach's Alpha	Comments
Business Plan and Vision (BPV)	5	0.876	Accepted
Management Support (MS)	5	0.872	Accepted
Champion (CH)	5	0.868	Accepted
Resources (R)	3	0.804	Accepted
Project Management (PM)	4	0.840	Accepted
Team Skills (TS)	6	0.903	Accepted
Change Management (CHM)	3	0.814	Accepted
Data Source Systems (DSS)	3	0.822	Accepted
IT Infrastructure (ITI)	3	0.836	Accepted
Attitude Toward Technology (ATT)	4	0.899	Accepted
Trust (T)	3	0.895	Accepted
System Quality (SQ)	9	0.933	Accepted
Information Quality (IQ)	9	0.962	Accepted
Decision Quality (DQ)	4	0.938	Accepted
Overall (all constructs)	66	0.973	Accepted

4.6.3 Approach to sampling

Sampling is a process by which there is the selection of a suitable number of targeted elements from a population that reflect the interests of the research (Sekaran and Bougie, 2016). Sampling also has the aim of establishing clear criteria for the exclusion and inclusion of samples through description of the key characteristics for the research respondents targeted. Sampling is a process that is key to the entire data collection stage, since it determines the data quality and research feasibility (Creswell and Creswell, 2017). Furthermore, an essential characteristic of quantitative research is employing a sample that is a reflection of the attributes of the target population (Sarandakos, 1998). The research sample is taken from the population for which there will be a generalisation of the study results (Bell et al., 2018). During the selection of a sample where it is important that the results can be generalised, it is vital that an unbiased population subset is selected (Collis and Hussey, 2014; Bell et al., 2018) this permits the sample results to address the question of the research, and also to be generalisable to the whole population (Collis and Hussey, 2014). For Cooper and Schindler (2014), the study purpose and scope are vital during the selection of an appropriate sample.

4.6.3.1 **Sampling techniques**

Prior to undertaking the collection of data, researchers have to give consideration to the sampling technique in order to enable the acquisition of data that is appropriate. For Bryman (2016), the determinants of the frame of sampling are the research question(s) and objectives. Sekaran and Bougie (2016) assert that once the target population has been identified, the researcher has to categorise the sample through the application of an appropriate technique. Sample designs can be of either a non-probability or probability nature (Collis and Hussey, 2014). It is vital to select a sample design that is appropriate for the reduction of bias within the sample selected, with the elimination of sampling errors and estimation of the possible sampling range (Gill and Johnson, 2010). Probability sampling is used within quantitative research, whilst non-probability sampling is employed within qualitative research (Leslie and Caldwell, 2016). Probability sampling has the aim of representing the entire population, and including a selection of random subject samples from a particular population, or from a specified strata or subgroup from a population (Leslie and Caldwell, 2016; Creswell and Plano Clark, 2018). Probability sampling could include systematic sampling, random sampling, cluster sampling, double sampling, stratified sampling and stage sampling (Sekaran and Bougie, 2016; Bell et al., 2018; Easterby-Smith et al., 2018). Meanwhile, non-probability sampling is a technique whereby the research sample members are chosen in a way that does not give an equal chance for all of the target population members to be chosen (Bryman, 2016). With this particular technique, the research sample units are frequently selected according to their availability or the judgement of the researcher(s) (Creswell and Creswell, 2017). Non-probability sampling could include purposive sampling, snowball sampling and convenience sampling (Collis and Hussey, 2014; Bell et al., 2018). The technique of non-probability sampling is more effective in relation to time and costs in comparison to probability sampling. Moreover, it is important to underscore that non-probability sampling has practicality when the study population is extremely large or unlimited, or when it is impossible to determine the probability that every respondent or unit will be included within the sample (Collis and Hussey, 2014; Cooper and Schindler, 2014; Creswell and Creswell, 2017; Bell et al., 2018).

The selection of the method of sampling depends on the study nature, the resources of time and money, and the availability of the sample (Newbold et al., 2013). This study focuses on decision-making at all forms and levels of management, regardless of the managerial level of the decision-makers. Therefore, in this research project probability sampling was adopted through the simple random sampling technique, which involves the equal probability of selection for each of the element numbers (Bryman, 2016). The technique involves the selection of the sample in a random manner from within a frame of sampling, with the use of an algorithm of random numbers, whereby each unit of the population that is accessible has an equal chance of inclusion within the sample (Sekaran and Bougie, 2016; Creswell and Creswell, 2017). Utilising random numbers permits the selection of the sample without bias, so that it can be assured that the sample is truly representative of the study population (Sekaran and Bougie, 2016). Simple random sampling has the primary benefit of affording protection against bias in selection through providing a guarantee that the sample selection is representative of the study population, provided that the size of the sample is not extremely small (Bell et al., 2018).

4.6.3.2 **Sample size**

Any study employing a survey has to account for the size of its sample, or in other words, the number of included entities (Collis and Hussey, 2014; Bell et al., 2018). The size of the sample is dependent upon financial considerations and the time available (Bell et al., 2018); however, employing a survey requires the selection of the largest possible sample size (Collis and Hussey, 2014), since a large sample will provide a better reflection of the entire population and to a greater degree of precision than a small sample (Creswell and Creswell, 2017; Bell et al., 2018). A large sample is also suggested since a positivist philosophy has its focus on the formulation of hypotheses, with the establishment of facts that are objective, and the discernment of the causalities and relationships between such facts (Creswell and Creswell, 2017). Moreover, a large sized sample is needed when undertaking statistical analyses (Bell et al., 2018). All of the aforementioned criteria are met in this study, which uses structural equation modelling (SEM) for the analysis of the conceptual framework proposed; therefore, a large size of sample was required (Hair et al., 2018). Bernard (2013) recommends that at least five responders are selected for each construct, and over 100 participants included for each data analysis. Moreover, the sample of the calculation ought to be at least 5% of the population (Newbold et al., 2013). Hair et al. (2018) consider it appropriate to have a minimum sample size of 200 in order to ensure the SEM is robust. SEM also has sufficiency if the size of the sample is at least 250 and the data that is missing is lower than 10% (Hair et al., 2018).

Since this study aims to investigate those implementation factors that have a bearing upon BI success within the mining sector in Jordan, the population of the research includes all those within the industry who are in positions for decision-making. Within the survey, decision-makers (managerial staff) were targeted who had sufficient competency to answer all the questions. A broad description of a study population is that it is the total unit numbers from which the data for the research may be acquired. Specifically, the research population can be described as all those individuals who have met the study criteria for participation (Collis and Hussey, 2014). The sample frame (population size) used within this study was acquired from the database of the General Trade Union of Workers in Mining and Metal Industries for Jordan. The population comprised 2,074 decision-makers registered to work and practice within the Jordanian mining sector. Through Yamane's (1967) formula for achieving a representative sample, the sample size for this research project was found to be 335 managers. In order to ensure that the minimum sample size of 335 would be attained, it was decided that 500 questionnaires needed to be distributed to allow for those questionnaires that were unusable (e.g. incomplete) or not completed. For the selection of the required sample with representativeness for the population, the population details were exported and coded into a Microsoft Excel spreadsheet. Then, the RAND function was used as a technique for generating a random sample from the population that had been coded.

4.7 Data analysis

4.7.1 Data screening

In general terms, a precondition for the analysis of data is data accuracy. Errors with data may occur at the level of both the researcher and the respondent; for example, the former could enter data erroneously such as within the wrong row or column, while the latter could enter incorrect information such as typing 1 instead of 10 (Sekaran and Bougie, 2016; Hair et al., 2018). Although the errors from data entry were expected to be minimal due to the use of a web-based survey technique, there was thorough screening of the data, including the handling of missing data, the checking of outliers and checking for normality, reliability and multicollinearity, since all of these could have an impact on the analysis, and therefore on the quality of the findings (Byrne, 2016; Gurnsey, 2017).

- **Missing data**

Missing data are known as the data values not stored for a particular variable of interest within the observation (Bell et al. 2018). For particular variables, missing data show there is a problem with the measurement that calls for a solution (Urdan, 2016). Creswell and Creswell (2017) argue that missing data occurs due to response problems, errors whilst entering the data or with large samples. Some treatments are able to solve the problem of missing data, but several factors are involved in selecting a technique that is appropriate. The selection of a technique for minimising the amount of missing data is influenced by its causes, the user types, the number of values that are missing and the size of the sample (Bryman, 2016). Any remedy suggested for addressing the issue of missing data is likely to yield biased results if the absent data are non-ignorable or not random.

If the missing data are random, however, then any technique employed is likely to give acceptable results (Kline, 2015). Different approaches exist for addressing the issue of missing data such as pairwise deletion, list-wise deletion, conditional mean estimation, mean substitution, regression-based imputation, multiple imputations and imputation through the use of the algorithm of expectation-maximisation (Williams et al., 2009; Argyrous, 2011; Blunch, 2012; Hair et al., 2018). The most widely used approach is mean substitution, since it is the most suitable method for the replacement of missing values and it avoids the deletion of such cases, with its subsequent reduction in the size of the sample (as would be the case when using the other methods) (Bell et al., 2018). Case-wise or list-wise data deletion also has the potential to reduce the sample size (Tabachnick and Fidell, 2019). The method of mean substitution should not to be used if the number of missing values is high (Tabachnick and Fidell, 2019). Therefore, when the number of questions not answered by a particular respondent is high, it is more preferable for that questionnaire to be removed. However, mean substitution may be used for the replacement of missing values if only a few items remain unanswered. Within this study, only a low number of data values were missing. Therefore, the decision was made, as Hair et al. (2018) recommend, to employ mean imputation substitution.

- **Outliers**

The term 'outliers' refers to scores that are very different from others (Byrne, 2016). Tabachnick and Fidell (2019) note four primary reasons for the occurrence of outliers: i) the incorrect entry of data; ii) because missing data were considered as actual data and included; iii) the sample is representative of the population concerned, since there has been an error with the sampling; and iv) variable values are included that are beyond the normal distribution range. There are two kinds of outlier: multivariate and univariate. A multivariate outlier occurs when there exists a strange value combination in at least two variables, while a univariate outlier arises when a value exists that is extreme in one variable (Blunch, 2012; Byrne, 2016; Tabachnick and Fidell, 2019). Tabachnick and Fidell (2019) recommend that univariate outliers can be examined through either the criteria from statistics by the calculation of the z score (standard score) for each of the variables, or through inspecting the values visually through graphical methods such as box plots and histograms. Within this study, univariate outliers were examined through the use of an approach known as the BoxPlot (Box and Whisker) method. Tabachnick and Fidell (2019) argue that examination of multivariate outliers must be undertaken following the examination of univariate outliers since univariate ones could become multivariate ones if at least two variables are combined. They assert that the Mahalanobis distance can be one kind of measure for that multivariate kind of distance, with this potentially evaluated for each of the cases through the distribution of X^2 (Tabachnick and Fidell, 2019). On that basis, for this study each respondent case was examined for outliers of a multivariate kind through the Analysis of Moment Structures ([AMOS], v.25) software for the calculation of D^2 (Mahalanobis's distance squared), as Kline (2015) recommends, for a probability that is lower than 0.001 ($p<0.001$).

- **Normality**

'Normality' is a term referring to the degree to which a sample data distribution is in correspondence with a normal distribution (Sekaran and Bougie, 2016). If it is demonstrable that variables have univariate normality, then there is an assumption of multivariate analysis (Bell et al., 2018). Normality violation could affect the process of estimation or interpretation of the results, particularly during SEM analysis; for example, it could increase the value of chi-square and potentially lead to underestimation of the indices for fit and the parameter estimates for standard errors (Byrne, 2016). Normality can be determined through graphical analyses or visual checks such as a plot of normal probability and a histogram in order to be able to compare the data values observed with an approximate normal distribution. If the distribution of the data observed follows along diagonal lines, then there is considered to be normality to the distribution (Byrne, 2016). Normality testing is vital in order to decide if non-parametric or parametric tests are suitable for the dataset. As Urdan (2016) recommends, parametric tests may be used when certain assumptions are met by the data. One such assumption is that the data are taken from a population that has a normal distribution (Urdan, 2016).

The normality of a distribution may be described through the use of two kinds of measure: skewness and kurtosis (Kline, 2015). The term 'skewness' refers to the degree of distribution symmetry about the mean. In a distribution that is positively skewed, the long distribution tail travels on the right-hand side along the horizontal axis towards values that are higher. When there is a positive skew to the distribution, the mean has a value that is greater than that of the median, which is itself larger than that of the mode. The converse is that a negatively skewed distribution has its long tail to the left-hand side along the horizontal axis, pointing towards the values that are lower; in this case, the mean has a value that is lower than that of the median, which is itself lower than that of the mode (Newbold et al., 2013; Kline, 2015). Kurtosis, on the other hand, refers to the peakedness or flatness in a distribution when compared to a distribution that is normal (Hair et al., 2018). A positive kurtosis is an indication that a distribution has more peaks than a distribution that is normal, whilst a negative kurtosis indicates that a distribution has fewer peaks than a distribution that is normal (Urdan, 2016). A distribution that is normal has a score of zero for both kurtosis and skewness. If the skewness value is less than -1 or higher than +1, the scores for kurtosis outside ± 2 times the standard error it has, and the rating for skewness is outside ± 1 times the standard error it has, then this is an indication that there is non-normality to the data (Kline, 2015). Hair et al. (2018) argue that the critical value used most commonly for skewness and kurtosis testing is ± 2.58. Within this study, the normality of the data was checked through evaluation of the values for skewness and kurtosis via SPSS (v.25). Furthermore, a maximum acceptable observation limit for the skewness and kurtosis testing in this study was set by the researcher at ± 2.58.

- **Multicollinearity**

The term 'multicollinearity' refers to a situation where at least two variables are very closely related in a linear manner (Tabachnick and Fidell, 2019). It is important to examine multicollinearity for regression analysis as the existence of multicollinearity within the model of regression leads to a reduction in prediction ability (Newbold et al., 2013). As Hair et al. (2018) note, two multicollinearity components are used in testing variable correlations that are multiple and pairwise: the factor of variance inflation and tolerance. Tolerance refers to the variability amount in independent factors, implying that other independent factors have not been explained (Hair et al., 2018). The variance inflation factor (VIF) demonstrates whether a predictor is in a strong linear relationship with the other kind of predictors (Field, 2017). The VIF is calculated as being the tolerance inverse (1/tolerance). The value of acceptance for multicollinearity is that a tolerance ought to have a value lower than 0.10 or a value for VIF that is higher than 10 (Field, 2017; Tabachnick and Fidell, 2019), and if multicollinearity is shown for at least one of the large factors of variance (Argyrous, 2011). If a VIF has a value higher than 10, then this indicates that the regression coefficients that are associated with them have been poorly estimated due to multicollinearity (Kline, 2015). Within this research, the VIF test was undertaken using SPSS (v.25) in order to check the multicollinearity, with Chapter 5 presenting of all of the results (Section 5.2.4).

- **Reliability**

The reliability is a measure of the extent to which an indicator set for a latent construct has internal consistency within its measurements (Gurnsey, 2017). Indicators for constructs that are highly reliable ought to be interrelated (Field, 2017). The examination of reliability has great importance in ensuring that there is a high stability score, good research consistency and that any measurement errors are avoided (Kline, 2015). Two commonly used indicators for the reliability of a scale are internal consistency and temporal stability (test–retest reliability) (Sekaran and Bougie, 2016). The assessment of test–retest reliability is carried out through its administration to the same assessed people on two different occasions, following which a calculation is made of the correlation that exists between the two obtained scores (Creswell and Creswell, 2017). On the other hand, the reliability scale for internal consistency involves the assessment of the extent to which items comprising the scale are all measuring the same underlying attribute (Bell et al., 2018). The measure for internal consistency most often used is the reliability test known as Cronbach's coefficient (α) alpha from Cronbach (1951). Cronbach's alpha, which is also referred to as coefficient alpha, provides an assessment of the entire scale consistency (Urdan, 2016). The statistical measure investigates the extent to which there is consistency in the answers across all of the items in a singular measure (Kline, 2015). If the reliability of internal consistency is at a low level, there could be heterogeneity in the item content, and the totalled score will not represent the optimum analysis unit for the measure (Kline, 2015). Good reliability is suggested by an estimate of reliability with a value of 0.70 or above. Reliability with a value from 0.60 to 0.70, on the other hand, may show acceptability, as long as other indicators for the construct validity of a model are good. The lowest limit that is acceptable for the Cronbach's coefficient (α) is 0.70 (Churchill, 1979). Within this research project, there was assessment of the Cronbach's alpha values to check the reliability of the data through the use of SPSS (v.25), with the results presented in Chapter 5 (Section 5.2.5).

4.7.2 Descriptive analysis

Descriptive statistics help in providing descriptions of sample characteristics within a report method section (Gurnsey, 2017), with a statistical tool set helping researchers to accurately describe large data volumes through the use of only a few values (Newbold et al., 2013). Descriptive analysis could include the percentage, frequency and a measure for central tendency (e.g. the mean), as well as dispersion measures (variabilities) such as the minimum and maximum scores, the standard deviation (SD) and further information with regard to the score distribution (Tabachnick and Fidell, 2019). In terms of the percentage and frequency tables, the number of individuals that belong to each category is provided for a variable in question, and this may be utilised with regard to all multiple variable types (Sekaran and Bougie, 2016). The mean is a commonly used measure of central tendency that was used within this study. Essentially, the mean is an average that is the summation of all the distribution scores, which is then divided by the score number (Field, 2017). Within this research, the mean was calculated for all of the variables of ratio/interval, since it is a commonly used measure for that kind of variable (Bryman, 2016). Furthermore, the clearest and most popular kinds of technique for the measurement of dispersion are the SD and the range (Urdan, 2016). The range is the difference between the minimum (lowest) and maximum (highest) data values (Hinton, 2014), while the SD is the most-frequently used method of measuring variability in a dataset, since it provides a good view of how the data are distributed, although it can still be influenced by outliers (extreme scores) (Sekaran and Bougie, 2016). Within this research, descriptive statistics were employed in describing the key study sample characteristics through the use of SPSS (v.25), with all the descriptive statistics shown in Chapter 5 (Section 5.3).

4.7.3 Structural equation modelling

SEM is a suitable technique for the accurate testing of theory and the building of empirical models (Blunch, 2012). SEM helps in estimating interrelated and multiple relationships of dependence (Williams et al., 2009), and can represent the unobserved concepts of those relationships whilst also accounting for the error in measurement within the process of estimation (Argyrous, 2011). It permits the representation of constructs by numerous measures, and thus provides the researcher with a more valid and realistic way of operationalising constructs (Byrne, 2016). Therefore, SEM enables the researcher to identify relationships once account has been taken of measurement error (Gefen et al., 2011; Byrne, 2016).

As this study project involves the estimation of interrelated and multiple relationships of dependence, where the techniques of analysis have been associated with particular advantages (as discussed above), SEM was selected ahead of other multivariate techniques for the testing of the model and the hypotheses. The approach integrates path analysis and factor analysis (in addition to multivariate techniques), and thus can put forward lean explanations of the correlations that are hypothesised between the constructs within a theoretical model (Argyrous, 2011; Blunch, 2012; Byrne, 2016; Hair et al., 2018). The SEM technique offer a flexible approach and it can be used for the analysis of both non-experimental and experimental data, whilst simultaneously hypothesis testing (Kline, 2015; Byrne, 2016; Hair et al., 2018). The SEM process is described by Hair et al. (2018) as the development of a model that is theoretically based and constructs a diagram of the path for causal relationships, whilst facilitating the conversion of that path diagram to structural models and a measurement set, which interprets and modifies the model if it has been justified theoretically. Within this research, these steps were implemented in order to achieve a final model for the depiction of the significant relationships amongst the variables through which the study hypotheses could be tested. The reasons for the selection of SEM for the analyses of data were that it provides correction of the errors in measurement when undertaking the estimation of structural parameters, while providing a mechanism that is systematic in its validation of the relationships between indicators and constructs, and also testing the relationships amongst constructs within one single model (Williams et al., 2009; Kline, 2015; Hair et al., 2018; Tabachnick and Fidell, 2019). Furthermore, SEM gives the researcher complete control and fosters greater analytical understanding (Byrne, 2016), while offering rigorous, powerful statistical techniques to deal with complex models (Argyrous, 2011; Gefen et al., 2011; Kline, 2015; Byrne, 2016; Hair et al., 2018; Tabachnick and Fidell, 2019).

Therefore, SEM techniques were considered most appropriate for this study as it involves multiple dependent/independent relationships hypothesised within the proposed model of research (as described within Chapter 3). SEM comprises two parts: i) the measurement that links the latent variables to the observed ones through the means of confirmatory factor analysis (CFA), and ii) the structural model that links the latent variables to other kinds through means of simultaneous equation systems (Byrne, 2016; Hair et al., 2018). This study employs the 2-step SEM process, namely a measurement model and another structural model, in order to provide an enhanced empirical means of examining the models of theory (Hair et al., 2018). Both the measurement and structural models were evaluated through estimation techniques of maximum likelihood provided within the AMOS (v.25) software (Hair et al., 2018; Tabachnick and Fidell, 2019). The technique of estimation involves determination of the value of the unknown parameters and the error that is associated with the value estimated (Williams et al., 2009). Various methods of estimation are available such as generalised least square, maximum likelihood estimation, unweighted and weighted least square, ordinary least square and asymptomatically distribution-free approaches (Blunch, 2012).

The selection of a suitable technique of estimation is dependent upon the size of the sample, assumptions of independence and the degree of plausibility for the normality (Gefen et al., 2011). For this research, the maximum likelihood method was used within the SEM analyses in order to evaluate the measurement model (Bollen and Long, 1993; Barrett, 2007; Kline, 2015; Hair et al., 2018; Tabachnick and Fidell, 2019), which has the ability to estimate the missing data values and improve the estimates of the parameters for reducing the function of the specified fit (Hair et al., 2018). Thus, the estimation method chosen was the maximum likelihood type, as suggested by numerous researchers (Hu and Bentler, 1999; Kline, 2015; Byrne, 2016; Hair et al., 2018; Tabachnick and Fidell, 2019). This method of estimation has features that include a larger sample size, multivariate normality for the distribution of the sample, the ability to test the validity of hypotheses (Bollen and Long, 1993; Barrett, 2007; Hooper et al., 2008; Kline, 2015; Hair et al., 2018; Tabachnick and Fidell, 2019). Furthermore, the method of maximum likelihood is believed to be a technique that is unbiased when under moderate multivariate normality violations with samples that are moderately sized and, for each of the unobservable variables, a 5-item minimum is used (Bollen and Long, 1993; Hair et al., 2018; Tabachnick and Fidell, 2019).

4.7.3.1 **Using confirmatory factor analysis for measurement modelling**

In general, the statistical technique of factor analysis has the aim of looking for methods that may help in reducing and summarising data collected for small factor groups (Byrne, 2016). For Brown (2015), factor analysis forms part of a multivariate technique of statistics that aims to address the interrelationships between variables through the definition of a set of factors that are commonly underlying. Expressed another way, factor analysis involves the identification of representative variables from all of the variable groups, the creation of completely new variable groups that are lower in number, or the replacement of the original variable group (Brown, 2015). Hair et al. (2018) highlight that a major limitation of factor analysis relates to identified items for deletion that should not be removed since they form part of particular constructs that are representative of the study variables. The two primary approaches taken for factor analysis are the confirmatory approach and the exploratory one (Hair et al., 2018). Exploratory factor analysis helps in the representation of a large relationship number, amongst variables that are normally scaled, in a manner that is more straightforward (Brown, 2015; Hair et al., 2018; Tabachnick and Fidell, 2019). Moreover, exploratory factor analysis is employed in situations where the links amongst latent and observed variables are uncertain or unknown (Vandenberg and Lance, 2000; Byrne, 2016). With this kind of technique there is an exploration of the data, while providing the researcher with information regarding the number of factors required for the best representation of the data (Brown, 2015; Hair et al., 2018). As such, the analysis proceeds in a form that is explanatory in order to determine the manner in which the observed variables are related to the underlying factors and to what extent (Kline, 2015; Byrne, 2015).

CFA involves multivariate techniques for testing or confirming a relationship that has been pre-specified (Hair et al., 2018). CFA helps in establishing how well the measured variables are representative of a smaller construct number. Unlike exploratory factor analysis, CFA is suitable if the researcher has a degree of knowledge related to the underlying latent variable structure (Byrne, 2008; Schmitt and Kuljanin, 2008; Blunch, 2012). As such, it is essential that there is prior knowledge of the relationships expected amongst the factors and items, prior to the conducting of CFA, and thus there is the use of the ‘confirmatory’ term (Argyrous, 2011). Furthermore, CFA is a technique with lots of importance for SEM (Kline, 2015). Expressed differently, CFA is employed to provide confirmatory tests of the measurements of theory, and so it may not be undertaken without theory of measurement (Hair et al., 2018). Moreover, a combination of construct validity test and CFA techniques can lead to an enhanced understanding of measurement quality (Hair et al., 2018; Tabachnick and Fidell, 2019). Within this research project, there is the deduction of the variables observed for the constructs from previous studies with relationships that were pre-specified within the literature. As such, CFA through the use of AMOS (v.25) was undertaken for testing and confirmation of the relationships amongst observed the items (or variables) and factors (hypothetical constructs) or latent variables (Vandenberg and Lance, 2000; Hair et al., 2018). Within CFA, two stages are employed in the evaluation of the measurement model: indices of goodness of fit, and measurement model construct validity (Hair et al., 2018).

1. Goodness-of-fit indices

Each of the models of measurement and structure ought to be subject to assessment of the overall fit of the model so that a decision can be made of whether the model adequately represents the causal relationship set or not, which is typically undertaken through assessment of the measures for goodness of fit (Brown, 2015). Goodness of fit refers to a measure for a model in order to observe the data, including the R^2, the squared multiple correlations of multiple correlations within the multiple regression, analogues for R^2 within other models of regression, and indices for fit within SEM (Hooper et al., 2008). Rules of thumb are provided by goodness-of-fit indices, such as the values of cut-off for assessment of fit, and thus they should also be given consideration (Satorra and Saris, 1985; Barrett, 2007; DeVellis, 2016).

There are three kinds of measure for goodness of fit: parsimonious fit measure, incremental fit measure and absolute fit measure (Hair et al., 2018). Indices of absolute fit measure the degree to which the model proposed successfully reproduced the data observed (Hair et al., 2018), offering a direct assessment of how well the model fits to the data observed (Hu and Bentler, 1999). Their assessment is only of the overall model fit (both the measurement and structural models combined), without comparison to any other kind of model. Measures of absolute fit include the Goodness-of-Fit Index (GFI), the Chi-square statistic (X^2), the standardised root mean residual, and the root mean square error of approximation (RMSEA), in addition to the chi-square ratio (χ^2) to the degree of freedom that a model has and Adjusted Goodness-of-Fit Index (AGFI) (Argyrous, 2011; Kline, 2015; DeVellis, 2016; Hair et al., 2018).

Incremental indices of fit give a comparison of the proposed model to some other alternative model serving as a baseline, often known as the null model (Hair et al., 2018). Indices of fit that employ comparative statistics place a hypothesised kind of model somewhere along this continuum (Blunch, 2012; Byrne, 2016; Hair et al., 2018; Tabachnick and Fidell, 2019). The independent model sits at one continuum extreme and it corresponds to variables that are completely unrelated with degrees of freedom that equate to the data point number minus the estimated variances (Blunch, 2012; Byrne, 2016; Hair et al., 2018; Tabachnick and Fidell, 2019). Statistics of comparison include the Tucker–Lewis Index (TLI), the Comparative Fit Index (CFI), the Normed Fit Index (NFI) and the Incremental Fit Index (IFI) (Blunch, 2012; Byrne, 2016; Hair et al., 2018; Tabachnick and Fidell, 2019).

Parsimonious indices of fit provide information with regard to which of the models, among a competing set, is the best one with consideration for the fit in relation to the level of complexity. Furthermore, indices of parsimonious fit provide an evaluation of models that are completed, with inclusion of the Adjusted Goodness-of-Fit Index (AGFI), the Parsimony Goodness-of-Fit Index and the Parsimony Normed Fit Index (Hooper et al., 2008; Hair, 2018; Tabachnick and Fidell, 2019). However, amongst scholars and researchers, no agreement exists in relation to a specific measure for the fitness for SEM (Vandenberg and Lance, 2000; DeVellis, 2016; Hair et al., 2018). For Barrett (2007), every kind of index provides a representation of a particular aspect of fit for the model proposed. Therefore, as a consequence, no choice of goodness of fit ought to be founded upon one index, and thus the decision to retain or reject a model should always be based on multiple indices of goodness of fit (Schmitt and Kuljanin, 2008; Brown, 2015; Kline, 2015). Therefore, Hair et al. (2018) recommend that various indices of fit should be employed, with three or four indices likely to provide sufficient evidence for the fitness of the model. Kline (2015) suggests that there ought to be a minimum set of various types of fit indices when findings are reported: i) χ^2 (the Chi-square statistic) with the corresponding freedom degrees and significance level; ii) the RMSEA with its corresponding confidence interval of 90%; and iii) CFI and standardised root mean square residual. Furthermore, Hu and Bentler (1999) recommend that when findings are reported within SEM, a two-index combination is used; for instance, the standardised root mean residual accompanied by an index chosen from the following four: IFI, CFI, RMSEA or NFI (Non-normed fit index. In order to check the goodness of fit for the data observed and to represent it, this study employed numerous indices and goodness of fit standards were applied for assessment of the fit of the model. Furthermore, assessment of those standards and indices was founded upon the suggestions that follow: the GFI ought to have a value of at least 0.80 (Etezadi-Amoli and Farhoomand, 1996); the AGFI a value of 0.80 or more (Segars and Grover, 1993; Chin and Todd, 1995; Etezadi-Amoli and Farhoomand, 1996; Gefen, 2000); the IFI and TLI (that equate to the index for non-normed fit) need to have a value of 0.95 or more (Hu and Bentler, 1999); the CFI a value of 0.90 or more (Bentler and Bonett, 1980; Hoyle, 1995); and the RMSEA ought to have a value less than 0.05 for a fit that is excellent, and less than 0.08 for a fit that is good (Browne and Cudeck, 1992). Details of the indices and their levels of acceptance are shown in Table 4.4.

Table 4-4 Overall GFI indices for CFA

Test	Recommended values	Achieved values
Chi-square divided by degrees of freedom (x^2/df)	$1.0 < x^2 / df < 3.0$	1.245
Goodness-of-fit Index (GFI)	≥ 0.80	0.849
Adjusted Goodness-of-Fit Index (AGFI)	≥ 0.80	0.829
Incremental Fit Index (IFI)	≥ 0.95	0.972
Tucker–Lewis Index (TLI)	≥ 0.95	0.969
Comparative Fit Index (CFI)	≥ 0.90	0.972
Root Mean Square Error of Approximation (RMSEA)	≤.08	0.026

2. Construct validity

The validity of a construct is an essential condition when developing and testing theory (DeVellis, 2016); it has a relationship to the measurement accuracy so that confidence can be provided that the measures of items taken from the sample have representativeness for the actual population's true score (Hair et al., 2018). For MacKenzie et al. (2011), there is greater validity if the fit between the items measured and the theoretical latent kind of construct is better. There may be examination of construct validity through the assessment of the discriminant validity and convergent validity (MacKenzie et al., 2011; Hair et al., 2018). Convergent validity represents the extent to which the variables observable for a particular construct share a higher variance proportion (Hair et al., 2018). The construct reliability estimation, the factor loadings and the average variance extracted (AVE) are employed for assessment of the convergent validity for all constructs (Hair et al., 2018). Furthermore, Hair et al. (2018) suggest that the ideal standardised estimates of loading ought to be at least 0.7, the estimation of the AVE ought to be higher than 0.5, and the estimates of reliability ought to be over 0.7 in order to demonstrate that the convergent validity is adequate. As such, for the assessment of convergent validity in this research project there were minimum cut-off criteria for the loadings at a value greater than 0.7, the AVE at a value greater than 0.5 and a reliability greater than 0.7. For the evaluation of convergent validity, CFA was performed using AMOS (v.25), with the aim of examining the loading factors for all of the items, the composite reliability and the AVE (Schmitt and Kuljanin, 2008; Brown, 2015; Hair et al., 2018). The discriminant validity assures the researcher that a constructed measure has empirical uniqueness and is representative of the phenomenon in question in a way that other measures within SEM are not capturing (Hair et al., 2018). If there is no establishment of discriminant validity, the constructs have a bearing upon variation for more than solely the variables observed that they have theoretical relationships to, and consequently the researcher is unable to ensure that there are real outcomes in support of the relationships hypothesised within the structural model, or that they result from the statistical analysis (Farrell, 2010). Byrne (2008) suggest that the achievement of discriminant validity occurs if a latent construct accounts for a greater amount of variance within its measured associated variables than that shared with other kinds of variables within the same model. For this condition to be achieved, each AVE of the construct ought to be compared with the squared correlations it has with other model constructs (Brown, 2015; Hair et al., 2018). Within this study, the assessment of discriminant validity was through comparison of the square root for the values of AVE to the estimate of correlation between the constructs through a reliable Microsoft Excel statistical tools package (Gaskin, 2016).

4.7.3.2 **The structural model**

This particular stage includes the structural model specification by discovering the relationships from one particular construct in comparison to another, based on the theoretical model proposed (Hair et al., 2018). The causal model or theoretical model are referred to as structural models, and within this stage, the researcher had to differentiate between constructs that are endogenous and exogenous (Hair et al., 2018). The independent variables should be referred to as exogenous constructs, while the dependent variables should be referred to as the endogenous constructs (outcomes). The examination of the theory is carried out through testing the impact that the exogenous variables has upon the endogenous variables (Brown, 2015; Hair et al., 2018; Tabachnick and Fidell, 2019). Models that are structural differ from models for measurement in that they have a focus that moves from relationships between the measured items and latent constructs to the magnitude and nature of the relationships amongst constructs. CFA is used to examine measurement models, with the conversion of the CFA based on the nature of the relationship between constructs by using single-headed arrows to represent the causal relationships that have been hypothesised, rather than the correlational relationships between the variables employed in CFA. The primary purpose in this stage is the development of a structural model for testing the theoretical model that has been hypothesised (Schmitt and Kuljanin, 2008; Hair et al., 2018). The hypothesised model (structural model), therefore, demonstrates relationships between constructs that are latent, as shown in Chapter 3. For Blunch (2012), the aim of the structural model is the specification of which constructs indirectly or directly impact on the values of the other model constructs. These structural model testing results can be found in Chapter 5 (Section 5.4).

4.7.4 Common method bias

The common method bias is examined to determine whether the common method variance in the study is a serious issue (Estabrook and Neale, 2013; Archimi et al., 2018). If using self-reported data, common method bias can exist, which has the potential to manifest in the case of data resulting from a survey (Fuller et al., 2016); the issue represents a concern in methodological terms in the application of survey research generally, or if duplicate data are collected from the same respondents (Podsakoff et al., 2012; Fuller et al., 2016). Two methods exist for the testing of common method bias: the Harmon's one-factor test, and the factor analysis variance ratio (Podsakoff et al., 2003). This research employed the factor analysis variance ratio method through SPSS (v.25) for the assessment of common method bias (Siemsen et al., 2010). The following conditions apply when using of the method: i) there is the existence of only one factor within the result of the factor analysis, and ii) one single factor accounts for most of the variance amongst the variables (Podsakoff et al., 2003; Siemsen et al., 2010; Archimi et al., 2018). Chapter 5 (section 5.4.1.3) presents the results related to the common method bias.

4.8 Research ethics

Ethics can be considered as involving decisions over what is wrong or right about certain behaviour. Similarly, the ethics in research has regard for the manner in which research is undertaken, and how the results are presented (Collis and Hussey, 2014; Sekaran and Bougie, 2016). Ethical research has importance, since harm to voluntary respondents/participants must be avoided, and anonymity and confidentiality provided for all involved (Bell et al., 2018). All ethical principles were considered for this research prior to the collection of data. Consideration was given to Liverpool John Moores University's Code of Research Ethics, which served as a guide when the study was being designed. The University Research Ethics Committee granted approval for the study on 24th March 2017 (Ref. 17/LBS/004). The recruitment of the participants was on a voluntary basis accompanied by informed consent, where they had the right to withdraw their participation at any point during the process. The participants were recruited for this study without the use of any kind of deceptive means. To conform with the requirements of the ethical guidelines, the cover letter that accompanied the questionnaire and stated the study purpose can be found in Appendix 3. This cover letter included the researcher's name, address and the university he attends so that the confidence of the respondents could be increased, and to ensure that they felt were clear about who they were engaging with through their responses (Cooper and Schindler, 2014; Sekaran and Bougie, 2016). The information gathered from the respondents was kept in confidentiality, and the records did not include any form of description that would enable the identification of the participant. After ensuring the privacy and confidentiality of the respondents, the results were stored in aggregate for when the study results would be reported. The personal information of the participants is not identifiable within any of the findings presented in this thesis. Furthermore, the collected data have not been utilised for any purpose other than the stated aim and objectives of the study, namely the undertaking of academic research to fulfil the PhD thesis requirements.

4.9 Chapter summary

This chapter has provided comprehensive descriptions for the methodology utilised in this particular research project. The study was described as being founded upon a positivist research philosophy with a deductive approach. In turn, this approach was linked to the use of a quantitative data collection method so that there could be testing of the hypotheses derived from the conceptual framework of the study. There was a presentation of the research strategy, discussion related to the constructs and scales of measurement, and description of the approach to sampling that was adopted. The use of self-completed web-based questionnaires was described in order to acquire data from a high number of decision-makers working in the Jordanian mining sector. SEM was justified for use within this project in order to discover the relationships, in statistical terms, between the items of testing for each of the factors, as well as amongst the dependent and independent variables. As such, AMOS (v.25) and SPSS (v.25) were selected for analysis of the quantitative data collected through the deployment of the questionnaire survey. Furthermore, consideration was given with regard to common methods bias and research ethics. Next, Chapter 5 presents the preliminary analysis results, as well as the results from the SEM.

Chapter Five: Data Analysis and Findings

5.1 Introduction

This chapter presents the analyses of the empirical, quantitative data. A questionnaire survey was devised for the collection of the data, as explained within Chapter 4, following the distribution of 500 questionnaires to decision-makers working in the mining sector within Jordan. Of the instruments completed by the participants, the 372 responses (74% response rate) were considered to be of a sufficient quality for use within the analysis of the data. Such data analysis facilitated in gaining an understanding of the impact that factors of implementation have upon BIS success within the mining sector in Jordan. A total of 66 items of measurement were employed, representing 15 constructs: business plan and vision, management support, champions, resources, project management, team skills, change management, data source systems, IT Infrastructure, attitudes toward technology, trust, user participation, system quality, information quality, and decision quality.

A complete justification for the research methodology was provided previously in Chapter 4, involving the application of a quantitative method with the data acquired through a questionnaire survey. This chapter features the analysis of the data and presentation of the findings. Before statistical analysis is undertaken, there must be proper checking and preparation of the data in order to ensure the necessary criteria have been met for the results to be dependable. That preliminary analysis involved data screening for missing data, outliers and checking for the normality, multicollinearity and the reliability coefficients for the scales of the instrument. The analysis of the data involves the descriptive statistical results, followed by a description of the respondents' profiles. Following this, there is a presentation of results from the testing of the validity of the constructs through CFA. Then, the structural model is tested through SEM. There is assessment of the measurement model on the bases of the overall fit of the model, and the validity of the constructs through CFA. SEM is employed in investigating the relationships between the dependent variables for BI success (i.e. system quality, information quality and decision quality) and the independent variables for the implementation factors of BI (i.e. the business plan and vision, management support, champions, resources, team skills, change management, data source systems, IT infrastructure, attitudes toward technology, trust and user participation). In the presentation of the conducted survey results for this study, SPSS (v.25) and AMOS (v.25) were utilised for the analysis of the raw data. This chapter comprises of five sections: the introduction, the data screening and descriptive analysis to illuminate the basic features in the data sample in section 5.2, the undertaking of CFA for the validation of the measurement model in section 5.3, the SEM for the validation of the structural model and the measurement of the relationships in section 5.4, with an overall chapter summary presented in section 5.5.

5.2 Data screening

5.2.1 Missing data

With multivariate methods, there is a need for completion in the data. Therefore, when employing SEM as the technique of data analysis, a critical issue is the matter of missing data (Argyrous, 2011; Blunch, 2012; Hair et al., 2018). Usually, missing data occurs due to problems around the collection or entry of data (Hair et al., 2018). In order to reduce the amount of missing data, Urdan (2016) recommend that researchers employ self-administered questionnaires that are well designed and that have been pre-tested extensively. As discussed in Chapter 4, the issue of missing data can be solved through the use of mean substitution (Hair et al., 2018), which is preferable if there is a relatively low quantity of missing data. Within this research, this was the case so it was decided to employ mean substitution, as recommended by Hair et al. (2018). Within this study, the missing value percentages ranged from 0.3% to 0.5%; for Hair et al. (2010), there may be the application of mean substitution when the value of missing data is below 10%. As such, and as strongly recommended by both Hair et al. (2018) and Tabachnick and Fidell (2019), the missing values within this study were substituted by the variable mean.

5.2.2 Outliers

As discussed in Chapter 4 (Section 4.7.1), outliers can be considered as extreme values of data when compared to others within the dataset, which may render the distribution of data to have non-normality and present difficulties for analysis that is regression-based (e.g. SEM). Within this research, all of the variables with relevance were measured through continuous variable questioning, employing a 5-point Likert scale, thereby necessitating examination of the multivariate and univariate outliers. In order to check if univariate data outliers were present, there was examination of a box plot for all of the variables. Through the use of the original data, there was found to be no univariate outliers present. Then, there was examination for the detection of multivariate outliers. On that basis, all of the cases of the respondents in this research were examined for multivariate outliers through the calculation of D^2 values, as outputted by AMOS (v.25) and shown in Table 5.1; the indication was that just two cases of outliers existed with p-values lower than the recommended <0.001 cut-off point, as noted in the work of Kline (2005).

Table 5-1 Detecting outliers

Observation number	Mahalanobis d-squared	p1	p2
190	120.991	.000	.016
113	117.156	.000	.001

Even though the removal of those cases of outliers may lead to the enhancement of the multivariate analysis, this could lead to negative effects on the result's generalisability (Tabachnick and Fidell, 2019). Moreover, small numbers of outliers will not cause problems (Kline, 2015). Therefore, the decision was made to keep these outliers.

5.2.3 Normality

The term 'normality' refers to the score distribution, and for the measurement of variables it is a key assumption. When data are being analysed, the normality is not always needed, but it is generally preferable if there is a normal distribution to the variables (Tabachnick and Fidell, 2019). Statistical methods can be used to assess data normality (Hair et al., 2018). Normality may be measured through the use of the tests for skewness and kurtosis, and the method known as the Kolmogorov–Shapiro test (Byrne, 2016; Bell et al., 2018). An indication of distribution symmetry is provided by skewness, whereas kurtosis demonstrates the degree to which a distribution is peaked. If there is positive skewness then there will be a clustering of scores to the left-hand side of the graph, whilst if there is negative skewness there will be a clustering of scores to the right-hand side of the graph. Positive scores for kurtosis will represent clustering at the centre. If the values of kurtosis are less than zero then there is a flat distribution with extreme cases. Moreover, the tests for skewness and kurtosis have sensitivity to the size of sample, and thus researchers suggest that the distribution shape is inspected through the use of a histogram (Tabachnick and Fidell, 2019). For Hair et al. (2018), the critical value most commonly used for the testing of kurtosis and skewness is ± 2.58. Within this research, all of the independent variables were assessed for normality through the use of the methods of skewness and kurtosis (see Table 5.2). All of the items were distributed normally, as shown in Table 5.2, with the lowest values registered for kurtosis and skewness being -1.048 and -1.129, and the highest values being 1.188 and 0.296.

Table 5-2 Normality assessment

Item	Skewness	Kurtosis	Item	Skewness	Kurtosis
BPV1	-0.562	-0.345	**TS4**	-0.366	-0.792
BPV2	-0.747	-0.329	**TS5**	-0.935	0.468
BPV3	-0.661	-0.656	**TS6**	-1.017	1.048
BPV4	-0.920	-0.036	**CHM1**	0.236	-0.826
BPV5	-0.779	-0.414	**CHM2**	0.039	-0.818
MS1	-0.622	-0.484	**CHM3**	0.296	-0.818
MS2	-0.436	-0.609	**DSS1**	-1.129	0.593
MS3	-0.564	-0.629	**DSS2**	-0.706	-0.180
MS4	-0.479	-0.856	**DSS3**	-0.558	-0.371
MS5	-0.693	-0.365	**ITI1**	-1.286	1.188
CH1	-0.625	-0.682	**ITI2**	-1.207	0.719
CH2	-0.644	-0.340	**ITI3**	-1.075	0.660
CH3	-0.732	-0.371	**ATT1**	-0.426	-0.584
CH4	-0.491	-0.563	**ATT2**	-0.455	-0.519
CH5	-0.567	-0.566	**ATT3**	-0.881	0.030
R1	-0.540	-0.703	**ATT4**	-0.804	-0.055
R2	-0.528	-0.740	**T1**	-0.459	-0.493
R3	-0.526	-0.714	**T2**	-0.530	-0.603
PM1	-0.615	-0.261	**T3**	-0.510	-0.377
PM2	-0.795	-0.231	**UP1**	-0.423	-0.760
PM3	-0.736	-0.217	**UP2**	-0.545	-0.644
PM4	-0.819	-0.067	**UP3**	-0.483	-0.834
TS1	-0.910	0.727			
TS2	-0.848	0.530			
TS3	-1.015	0.988			

5.2.4 Multicollinearity

Multicollinearity may occur if the variables observed that explain a latent variable have redundancy. The result is that redundant variables will not be required for the analyses and ought to be eliminated (Tabachnick and Fidell, 2019). It is highly recommended that multicollinearity is examined before analysis is undertaken, as its occurrence can pose a significant problem for research. If multicollinearity occurs, the regression variances increase, which makes it extremely difficult to predict which independent variables account for the R^2 variance within the dependent variable (Hair et al., 2018; Tabachnick and Fidell, 2019). As previously discussed in Chapter 4 (Section 4.7.1), so there can be assurance that the independent variables' variance has uniqueness and does not overlap with the explanations for the dependent variables, a diagnostic test for multicollinearity was undertaken using SPSS (v.25). Typically, estimation is undertaken through the use of the 'tolerance' value, which quantifies independent variable variability that has not been explained by other model constructs. An issue of potential multicollinearity is signified by a tolerance value that is less than 0.1. Furthermore, an issue of multicollinearity may be detected through the value for tolerance of VIF, with a VIF value greater than 10 suggesting the presence of multicollinearity (Argyrous, 2011; Field, 2017; Tabachnick and Fidell, 2019). The multicollinearity results are presented within Appendix 4, with the indication that no VIFs exceeded 10 and there were no tolerance values lower than 0.10. Based on the above description, this indicated that there would be no serious multicollinearity occurring amongst the variables.

5.2.5 Reliability

A significant test of internal consistency is the confirmation that the item set being employed in measurement of a factor (construct) has/exhibits a high level of homogeneity (Field, 2017). The data reliability or internal consistency evaluates the extent to which the degree of the items proposed for a particular construct are acquiring the required information (Gurnsey, 2017). Cronbach's alpha is the test that is a most common used for the examination of a measurement scale's internal consistency (Urdan, 2016; Bell et al., 2018; Hair et al., 2018). A high value for Cronbach's alpha for every construct implied that there is internal consistency amongst them, and that they measure the same construct content. Churchill (1979) suggests that an acceptable cut-off point is 0.7, while Bell et al. (2018) and Hair et al. (2018) propose that an acceptable threshold for Cronbach's alpha, in theoretical terms, is ≥ 0.70. For Hinton et al. (2004), four different reliability points exist: excellent (> 0.90), high (0.70–0.90), moderate (0.50–0.70), and low (< 0.50). The results for the analysis of reliability for all of the constructs are shown in Table 5.3.

Table 5-3 Reliability analysis results (Cronbach's alpha)

Construct	No. of items	Cronbach's alpha (α)	Reliability strength
Business Plan and Vision (BPV)	5	0.925	**Excellent**
Management Support (MS)	5	0.882	**High**
Champion (CH)	5	0.925	**Excellent**
Resources (R)	3	0.873	**High**
Project Management (PM)	4	0.860	**High**
Team Skills (TS)	6	0.836	**High**
Change Management (CHM)	3	0.866	**High**
Data Source System (DSS)	3	0.774	**High**
IT Infrastructure (ITI)	3	0.809	**High**
Attitudes Toward Technology (ATT)	4	0.887	**High**
Trust (T)	3	0.842	**High**
User Participation (UP)	3	0.854	**High**
System Quality (SQ)	9	0.945	**High**
Information Quality (IQ)	6	0.884	**High**
Decision Quality (DQ)	4	0.794	**High**
Overall (all constructs)	66	0.961	**Excellent**

As Table 5.3 shows, the reliability test revealed that the design of the questionnaire had a level of reliability that was high, since the values for α (Cronbach's coefficient alpha) for the constructs had a level over 0.774. The data collected were consistent and highly reliable, as the level of alphas for the instrument had a range from 0.774 to 0.945, with an overall score of 0.961. As such, all of the values were located above the minimum recommended level of 0.70 (Churchill, 1979; Sekaran and Bougie, 2016; Field, 2017; Hair et al., 2018). Therefore, it may be stated that no problem of consistency was revealed during this particular data analysis stage.

5.3 Descriptive analysis

This section presents the background information for the study participants and information with regard to their characteristics. The questions in this part of the questionnaire related to the age, level of education, level within management, area of function, technology used, level of experience, use of the system and the length of use. The results are shown and discussed within the subsections that follow.

5.3.1 Respondent demographics

5.3.1.1 Gender of respondents

Figure 5.1 and Table 5.4 illustrate that the majority of the respondents in the sample were male (80.1%, n=298), with females accounting for 19.9% (n=74) of the research sample. It was announced by the Department of Statistics for Jordan (2016) that the workforce in Jordan primarily comprises of 67% men and 33% women. This ration is thus approximately reflected in the study sample

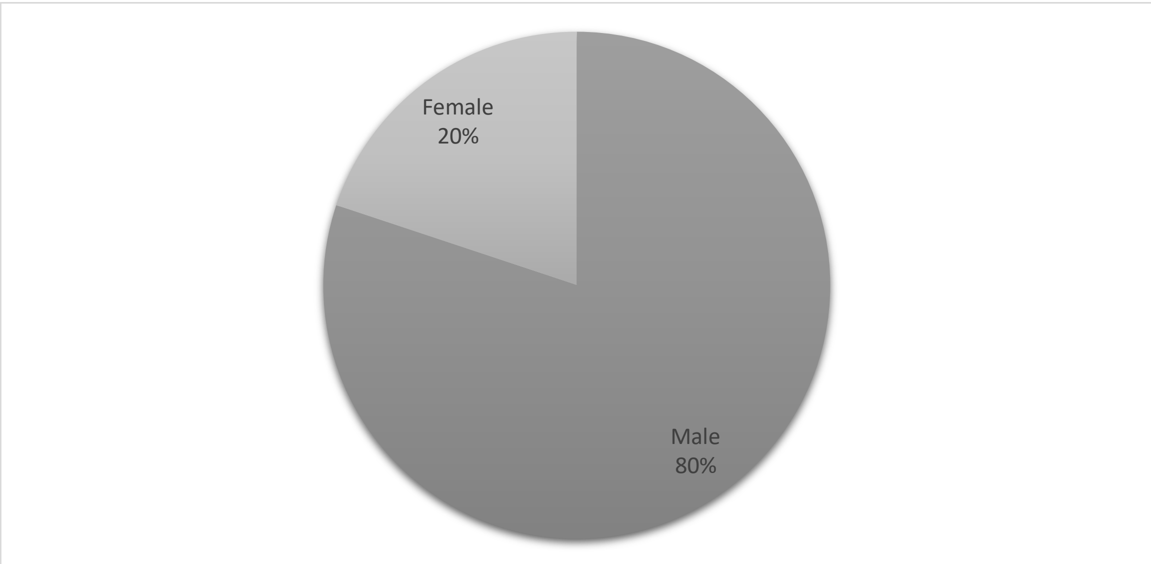

Figure 5.1 Distribution of respondents according to gender

5.3.1.2 Age of respondents

Most of the respondents (40.3%, n=150) were aged between 31 and 40 years, followed by those over 50 years of age (30.4%, n=113) and those aged 41–50 years (18.8%, n=70). Meanwhile, the lowest number of respondents was found to be those aged 21–30 years (10.5%, n=39), with none of the respondents aged 20 years or under (see Figure 5.2 and Table 5.4).

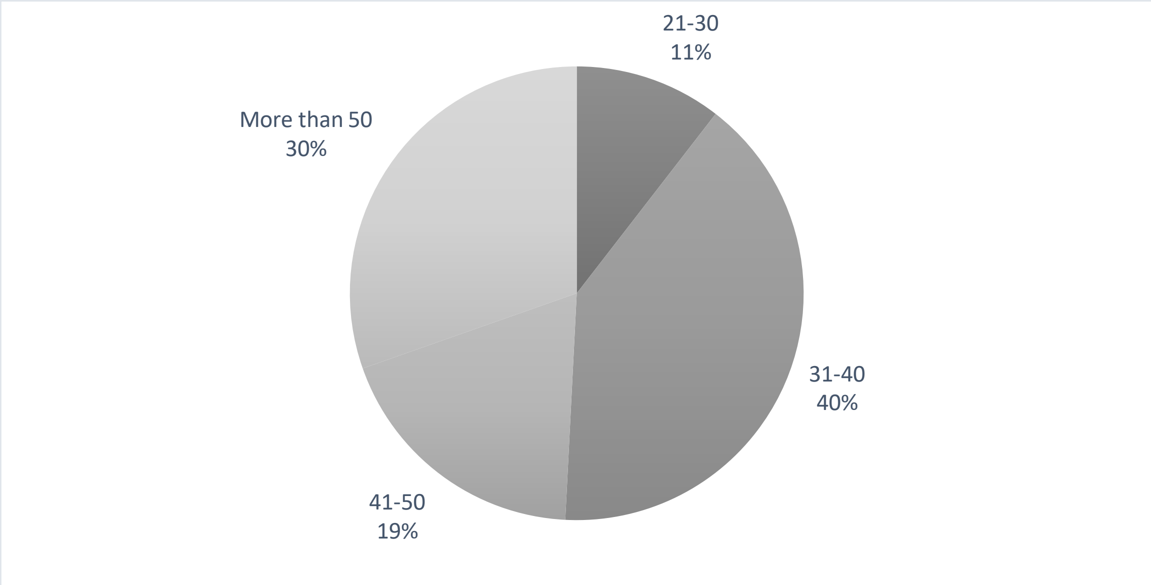

Figure 5.2 Distribution of respondents according to age

5.3.1.3 **Education level of respondents**

Over three quarters of the sample of the study had a Bachelor’s degree (89%, n=332 respondents), with a Diploma from a Community College held by 10% (n=37), a Master’s degree held by 1% (n=3), (see Figure 5.3 and Table 5.4).

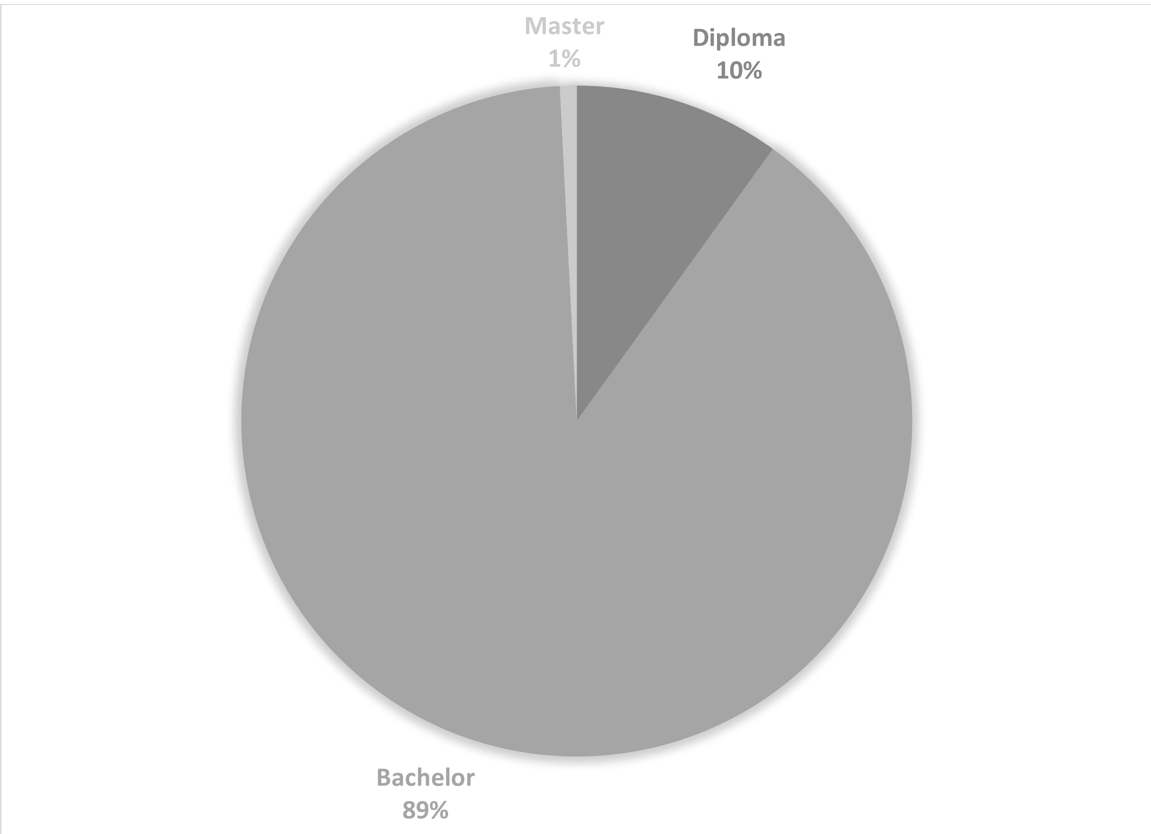

Figure 5.3 Distribution of respondents according to the level of education

5.3.1.4 Respondents' managerial level within the organisation

Over half of respondents worked at an operational level of management (55.1%, n=205), while the remainder worked at the middle management (33.6%, n=33.6) and the top management level. (11.3%, n=42) (see Figure 5.4 and Table 5.4).

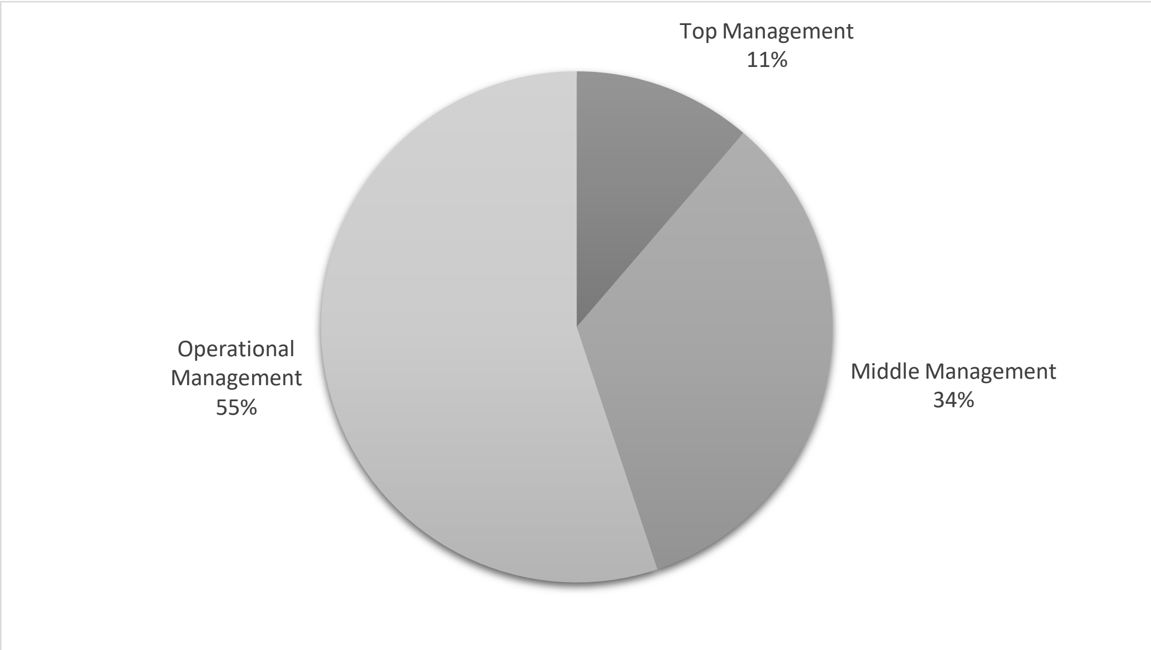

Figure 5.4 Distribution of the respondents in regard to their level of management within the organisation

5.3.1.5 Functional area of respondents

As shown by the descriptive statistics in Figure 5.5 and Table 5.4, the largest functional area was for the functional area IT (23.7%, n=88), followed by finance (16.9%, n=63), and then sales (13.2%, n=49) and marketing (11.3%, n=42), while 10.8% (n=40) of the research sample represented the area of business development, and 11% operations. Then, there was the human resources (6%, n=23) and legal functional areas (5%, n=20), while only 2.7% (n=10) of the respondents worked in the supply chain area. This indicates that key firm personnel (i.e. those expected to have awareness of key practices and terminology of IS and BIS) completed the survey questionnaire.

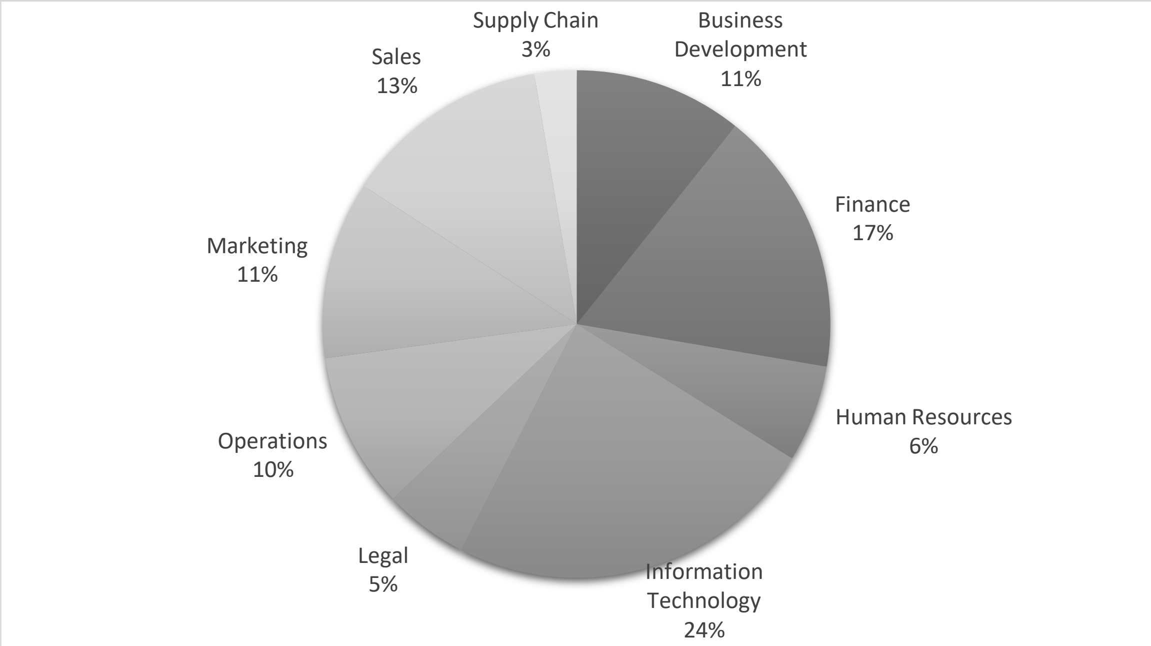

Figure 5.5 Distribution of respondents in relation to the functional area

5.3.1.6 **Respondents by implemented business intelligence software**

The largest number of respondents (40%, n=147) were in organisations that had implemented Oracle BI, followed by Microsoft BI that had been deployed in (27.4%, n=102) of the respondents' organisations, and a Reporting System implemented in 10.8% (n=40) of the organisations. Mix and Matched software had been implemented in 9.4% (n=35) of the organisations, and a Decision Support System implemented in 7% (n=26) of the organisations. Then, custom developed software had been implemented in 5.1% (n=19) of the organisations, and finally 0.8% (n=3) of respondents were in organisations that had implemented some other kind of BI software (see Figure 5.6 and Table 5.4).

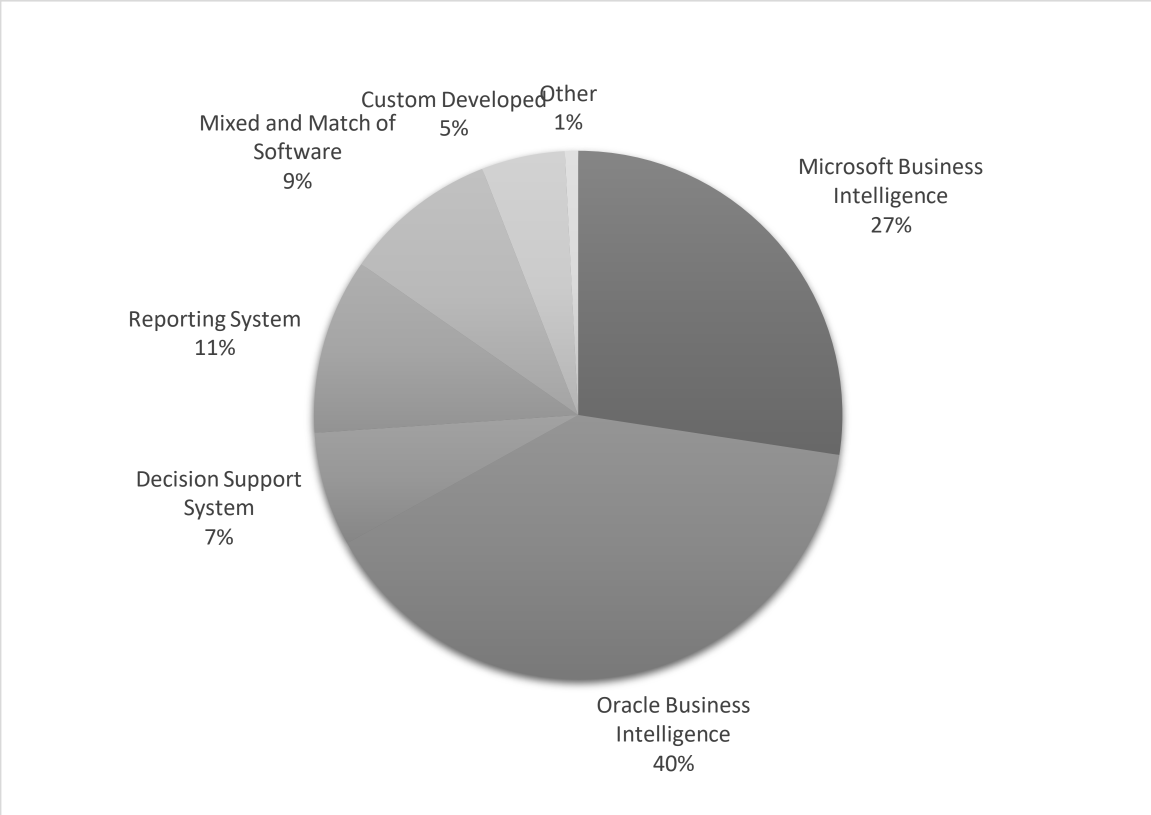

Figure 5.6 Distribution of the respondents based on the implementation of BI software

5.3.1.7 **Respondents by business intelligence usage and experience**

It can be seen from the analysis (see Figure 5.7 and Table 5.4) that 48% (n=180) of the participant sample reported that they had over five years' experience in using BI; 18% (n=67) noted that their usage of BI was 1–2 years; 12.9% (n=48) reported that they had been utilising BI for 3–4 years; 8.9% (n=33) of the respondents noted that they had been employing BI in their workplace for a period of less than six months; 8.3% (n=31) noted BIS usage of 4–5 years; and only 3.5% (n=13) had employed a system for BI for 6–12 months.

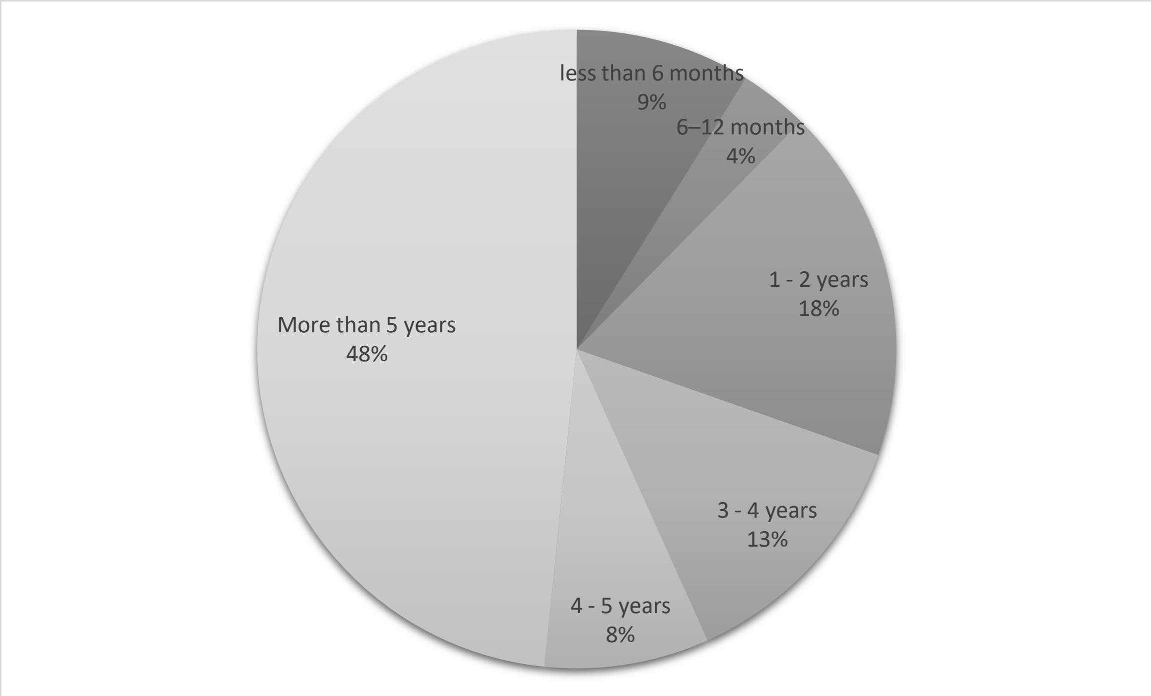

Figure 5.7 Distribution for respondents with regard to their usage of BI and experience

Table 5-4 Demographic profile of the respondents' results

Demographic profile		Frequency	Percent
Gender	Male	298	80.1
	Female	74	19.9
	Total	**372**	**100.0**
Age (years)	21–30	39	10.5
	31–40	150	40.3
	41–50	70	18.8
	More than 50	113	30.4
	Total	**372**	**100.0**
Education	PhD	0	0.0
	Masters	3	1.0
	Bachelors	332	89.0
	Diploma	27	10.0
	Total	**372**	**100.0**
Managerial level	Top Management	42	11.3
	Middle Management	125	33.6
	Operational Management	205	55.1
	Total	**372**	**100.0**
Functional area	Business Development	40	10.8
	Finance	63	16.9
	Human Resources	23	6.2
	Information Technology	88	23.7
	Legal	20	5.4
	Operations	37	9.9
	Marketing	42	11.3
	Sales	49	13.2
	Supply Chain	10	2.7
	Total	**372**	**100.0**
Technology used	Microsoft Business Intelligence	102	27.4
	Oracle Business Intelligence	147	39.5
	Decision Support System	26	7.0
	Reporting System	40	10.8
	Mix and match of software	35	9.4
	Custom developed	19	5.1
	Other	3	0.8
	Total	**372**	**100.0**
Length of use	less than 6 months	33	8.9
	6–12 months	13	3.5
	1–2 years	67	18.0
	3–4 years	48	12.9
	4–5 years	31	8.3
	More than 5 years	180	48.4
	Total	**372**	**100.0**

5.3.2 Analysis of variance

Analysis of variance (ANOVA) delivers techniques for comparing the differences among the means of more than two populations. The aim for determine variance in the analysis of variance is that the process for comparing the means involves investigating the variations in the sample data (Argyrous, 2011). Tabachnick and Fidell 2019 state that ANOVA enables the comparisons of two or more populations based on independent random samples. In this study, the One-way ANOVA test was used to test for significant differences between the dependent variable (decision quality) and demographic variables (Age, Education, Managerial level, Functional area, Technology used, Length of use).

Age

The Age group were divided into four groups when exploring the relationship between decision quality and age group, and as shown by the results presented in Table 5.5. From this, it can be seen that no statistically significant differences between the four age groups are evident (F (12, 359) =0.377; P< 0.971).

Table 5-5: ANOVA results for age groups.

		Sum of Squares	df	Mean Square	F	Sig.
Age	**Between Groups**	4.768	12	.397	.377	.971
	Within Groups	378.681	359	1.055		
	Total	383.449	371			

Education

The results of the ANOVA test to explore differences amongst the four different level of education level within the mining sector in Jordan, in terms of decision quality, Table 5.6 shows, no statistically significant difference between the groups in respect of the quality of decision making is evident when the one-way ANOVA (F (12,359) = 0.493; p = 0.919) is implemented.

Table 5-6: ANOVA results for education level.

		Sum of Squares	df	Mean Square	F	Sig.
Education	**Between Groups**	1.408	12	.117	.493	.919
	Within Groups	85.516	359	.238		
	Total	86.925	371			

Managerial level

The managerial level was divided into three groups when exploring the relationship between decision quality and managerial level, and as shown by the results presented in Table 5.7, no statistically significant difference was evident between the groups, as shown by one-way ANOVA testing (F (12,359) = 1.277; p = 0.230).

Table 5-7: ANOVA results for managerial level.

		Sum of Squares	df	Mean Square	F	Sig.
Managerial level	**Between Groups**	7.188	12	.599	1.277	.230
	Within Groups	168.390	359	.469		
	Total	175.578	371			

Functional area

The functional area was classified into nine groups when exploring the relationship between decision quality and functional area, and as revealed by the results presented in Table 5.8, no statistically significant difference was evident between the groups, as shown by one-way ANOVA testing (F (12,359) = 1.237; p = 0.255).

Table 5-8: ANOVA results for functional area.

		Sum of Squares	df	Mean Square	F	Sig.
Functional area	**Between Groups**	83.820	12	6.985	1.237	.255
	Within Groups	2026.854	359	5.646		
	Total	2110.675	371			

Technology used

The one-way ANOVA results presented in Table 5.9 show no statistically significant differences according to the technology used by the companies in the Jordanian mining sector with regard to the decision quality (F (12,359) = 0.741; p = 0.255).

Table 5-9: ANOVA results for technology used.

		Sum of Squares	df	Mean Square	F	Sig.
Technology used	**Between Groups**	71.789	12	5.982	.741	.255
	Within Groups	2896.824	359	8.069		
	Total	2968.613	371			

Length of use

The length of use BI was classified into six groups when exploring the relationship between decision quality and length of use, and as revealed by the results presented in Table 5.10, no statistically significant difference was evident between the groups, as shown by one-way ANOVA testing ($F(12,359) = 1.506$; $p = 0.120$).

Table 5-10: ANOVA results for length of use.

		Sum of Squares	df	Mean Square	F	Sig.
Length of use	**Between Groups**	50.823	12	4.235	1.506	.120
	Within Groups	1009.722	359	2.813		
	Total	1060.546	371			

5.3.3 Descriptive statistics for the items of measurement in each construct

In the model for the research, descriptive statistics for the means and SDs are noted for each of the constructs (variables) employed within the model of the research. The survey questionnaire was composed of 15 major constructs, measured using 66 different statements (items) through 5-point Likert scales with the respondents asked whether they disagreed or agreed with each of the statements, with the range from ‘strongly agree’ to ‘strongly disagree’. The responses were coded as follows: 1 indicated strong disagreement with what was stated in the particular statement, 2 indicated disagreement, 3 indicated a neutral view, 4 indicated agreement, and 5 indicated strong agreement. The midpoint was selected as being the value of 3 on the scale so that a distinction could be more easily made between the disagreement or agreement of the respondent. Descriptive statistics for the items of measurement for each of the constructs (variables) are considered within the following sections, with Table 5.5 presenting a description of the responses of the participants with regard to the primary proposed research factors.

Business plan and vision: Five questions (items) measured the business plan and vision construct. Those items measuring the implementation factors for the business plan and vision included the mission of the company and its goals, objective, strategies, quantified objectives and goals, realistic objective benefits and action plans (detailed). The mean scores for the five items employed in measuring the business plan and vision are shown through the results ranging from 3.081 to 3.223, with an SD range between 0.946 and 1.027. Therefore, the conclusion can be reached that most respondents were in agreement (i.e. with the mean score greater than the midpoint) with regard to a clear business plan and company vision helping an organisation in strategising its mission.

Management support: There was measurement of the management support construct through five statements (items). The average mean score was 3.276, which reflected the agreement of the respondents to the items. Further, the average SD had a value of 1.05, which was an indication of there being little dispersion from the mean score. In essence, the respondents were in agreement that the support of the management had a positive influence in regard to the use of BI within the Jordanian mining sector. Management support included encouragement for the utilisation of BI. The satisfaction of users has been a significant concern for management with a commitment to successful BI implementation, with them taking an active interest in the successes and problems with BI, and with regard to their provision of the resources necessary for the implementation of BI.

Champion: The measurement for the champion construct was carried out through five statements (items), with the results indicating that the champion plays a positive role in having an impact on projects, with an SD of 1.128, and an average mean score of 3.37. The highest agreement average (3.419) was for ‘The project champion encourages people to work as a team’ (CH2), while ‘The project champion encourages participative decision-making’ (CH4) had the lowest average at 3.312.

Resources: Within this study, three different items were employed in the measurement of the factors for the Resources construct. The construct item's mean score for the statement 'The business intelligence project was adequately funded' (R1) was 3.29, while for 'The business intelligence project had enough team members to get the work done' (R2) the mean score had a value of 3.199, and for the 'The BI project was given enough time for completion' (R3) the mean score value was 3.22. Using the 5-point Likert scale, all of the above three items were near the midpoint. The mean score average was 3.236, which indicates the agreement of the participants on the measures of the scale. In particular, the results show that most of the respondents were in agreement with regard to the resource availability for BI projects. The SD average was 1.163, which indicates a low dispersion amongst the scores of the respondents regarding the mean average.

Project management: There was measurement of the factors for the project management construct through four statements (items), with their average mean scores being 3.326 on the 5-point scale, which reflected the agreement of the respondents to those items. Also, with the SD average being 0.997, there was the indication of a small amount of dispersion around the mean score. The highest mean (3.414) was for the statement **'**Project management success in communicating between business intelligence implementation team members' (PM4), while the lowest mean (3.255) was for the statement 'Project management success in assessing project performance in the early stages of implementation' (PM1).

Team skills: The team skills construct was measured using six statements (items). Those particular items measuring the factor of implementation for team skills included the team having various areas of expertise; the team, including consultants, being technically equipped with the right skills for the BI; that there were good interpersonal skills amongst the team; the team were equipped with the kind of skills which were complimentary for one another; the team was composed of people with varied experiences; and the team had a variety of backgrounds in functional terms. The findings indicated that mean scores for the six items employed in measuring team skills ranged from 3.0 to 3.643, with an SD that ranged from 0.848 up to 1.036. The conclusion can be drawn that the majority of respondents (with the mean score over the midpoint) were in agreement that the team members ought to include the organisation's best staff.

Change management: The construct for change management was measured within this study by three statements (items). The statement 'The change management support was available whenever I needed it' (CHM1) had a mean score of 2.718, while 'The change management consultants understood my problems well' (CHM2) had a mean score of 2.726, and 'The change management consultants resolved the problems I faced' (CHM3) had a mean score of 2.618. It can be noted that for all three items, their values were below the midpoint on the 5-point Likert scale. The mean score average was 2.687, which showed a disagreement of the participants in relation to the measures of the scale. In particular, those results indicate that most respondents disagreed that the strategy for change management for recent reforms was suitable for the implementation of a BI project. The average SD had a value of 1.138, which showed a low level of dispersion amongst the scores of the respondents regarding the mean average.

Data source systems: The measurement of the data source systems construct was undertaken through five statements (items). The mean score average was 3.302, which reflected the agreement of the respondents in regards to the items. Moreover, the average SD was 0.919, which showed there was little dispersion about the mean score. The highest average was for 'Common definitions for key data items were implemented across the source system' (DSS1) with a value of 3.403, while the lowest average statement was for 'A significant number of source systems had to be modified to provide data for business intelligence' (DSS3) with a value of 3.242.

IT infrastructure: The respondents were asked for an indication of the degree to which they had an understanding of the adequacy and availability of the IT infrastructure for the implementation of a BIS within the mining sector within Jordan. The findings indicated that the three items used for measuring ITI had mean scores lying between the values of 3.344 and 3.57, with a range for the SD from 0.869 up to 0.933. The conclusion can be drawn that the majority of respondents (mean score at a level above the midpoint) were in agreement about the availability of IT infrastructure for the implementation of a BI project.

Attitudes toward technology: The participants' attitudes toward technology were measured using four questions (items). The mean score average for the items was 3.407 on the 5-point scale, which reflected agreement towards the items amongst the respondents. Furthermore, the average SD at a value of 1.081 showed there was little dispersion about the mean score. The averages varied within a range from 3.355 ‘Using a business intelligence system is a good idea’ (ATT1) to 3.446 for ‘Business intelligence system makes work more interesting’ (ATT2).

Trust: The measurement of the implementation factors with regard to the trust construct was undertaken through the use of three statements (items). The mean score average for the items was 3.262. Moreover, the average SD was 0.989, which showed little dispersion around the mean score. The highest average was for ‘I trust the transaction process on the business intelligence system’ (T3) with a value of 3.312, while the lowest average (3.215) was for (T2) ‘I trust the information presented on the business intelligence system’. The conclusion can therefore be drawn that the majority of respondents (mean score above the midpoint) were in agreement with regard to there being some degree of trust between the users and the system of BI.

User participation: The measurement of the user participation construct for the study was carried out through three statements (items). The mean scores for the questions were 3.234, 3.245, and 3.277 respectively, which were all above the midpoint of the Likert scale. The mean score average was 3.252, which showed the agreement of the participants with regard to the measures of the scale. In particular, the results indicated that the majority of the respondents were in agreement with regard to participation during the implementation of a BI project. Furthermore, the average SD was 1.099, which showed a low level of dispersion amongst the scores of the respondents regarding the mean average.

System quality: The measurement of the success factor for the system quality construct was undertaken through nine statements (items). The items of measurement included whether the system was reliable, whether it was easy to tell if there was correct system functioning whilst the integrity and security of data was maintained, it was easy for them to tell if there was correct functioning of the system, whether there could be easy adaption to new technology, whether maintenance was straightforward, it could be easily understood, whether it was straightforward to use and the functions of the system could be performed quickly. The mean score average was 3.525, which showed that there was agreement of the participants in relation to those measures of the scale. Moreover, the SD average was 1.102, which showed a low level of dispersion amongst the scores of the respondents regarding the mean average.

Information quality: In order for the success factor of information quality to be measured, six statements (items) were used, where the mean score average was 3.696. Furthermore, the average SD value was 0.78, which shows there was little dispersion about that score for the mean. The highest statement average of 3.844 was for ‘Information provided by the business intelligence system is in a useful format’ (IQ5), while the lowest average value of 3.522 was for ‘Through the business intelligence system, I get the information I need in time’ (IQ2). The conclusion can thus be drawn that the majority of respondents were in agreement with regard to the statements for information quality as the score for the mean was above the midpoint.

Decision quality: For the measurement of the decision quality construct, four statements questions (items) were used, where the scores for the mean at 3.893, 3.960, 4.013 and 4.167 were all over the midpoint. The score for the average mean was 4.008, which showed that there was agreement of the participants with regard to the measures of the scale. In particular, the results showed that most of the respondents were in agreement with regard to decision quality. Furthermore, the average SD of 0.712 showed there was a low dispersion of the respondents’ scores around the mean average.

Table 5-11 Descriptive statistics for the questionnaire measurement items

Construct	Item code	Mean	Standard deviation
Business Plan and Vision (BPV)	**BPV1**	3.145	0.946
	BPV2	3.151	0.960
	BPV3	3.081	1.025
	BPV4	3.223	0.972
	BPV5	3.191	1.027
	AVG_BPV	3.158	0.986
Management Support (MS)	**MS1**	3.293	1.050
	MS2	3.258	1.066
	MS3	3.280	1.055
	MS4	3.169	1.028
	MS5	3.384	1.051
	AVG_MS	3.277	1.050
Champion (CH)	**CH1**	3.328	1.204
	CH2	3.419	1.067
	CH3	3.406	1.061
	CH4	3.312	1.140
	CH5	3.387	1.168
	AVG_CH	3.370	1.128
Resources (R)	**R1**	3.290	1.176
	R2	3.199	1.115
	R3	3.220	1.200
	AVG_R	3.237	1.163
Project Management (PM)	**PM1**	3.255	0.900
	PM2	3.263	1.051
	PM3	3.374	0.978

	PM4	3.414	1.062
	AVG_PM	3.327	0.998
Team Skills (TS)	**TS1**	3.634	0.900
	TS2	3.548	0.872
	TS3	3.513	0.848
	TS4	3.000	1.036
	TS5	3.492	0.867
	TS6	3.643	0.907
	AVG_TS	3.472	0.905
Change Management (CHM)	**CHM1**	2.718	1.165
	CHM2	2.726	1.074
	CHM3	2.618	1.175
	AVG_CHM	2.687	1.138
Data Source Systems (DSS)	**DSS1**	3.403	0.928
	DSS2	3.263	0.884
	DSS3	3.242	0.946
	AVG_DSS	3.303	0.920
Information Technology Infrastructure (ITI)	**ITI1**	3.570	0.922
	ITI2	3.470	0.933
	ITI3	3.344	0.869
	AVG_ITI	3.461	0.908
Attitudes Toward Technology (ATT)	**ATT1**	3.355	1.050
	ATT2	3.446	1.116
	ATT3	3.393	1.050
	ATT4	3.436	1.108
	AVG_ATT	3.407	1.081
Trust (T)	**T1**	3.261	0.996
	T2	3.215	0.975
	T3	3.312	0.998
	AVG_T	3.263	0.990
User Participation (UP)	**UP1**	3.277	1.117
	UP2	3.234	1.065
	UP3	3.245	1.117
	AVG_UP	3.252	1.099
System Quality (SQ)	**SQ1**	3.581	1.097
	SQ2	3.546	1.031
	SQ3	3.557	1.028
	SQ4	3.637	1.114
	SQ5	3.554	1.054
	SQ6	3.729	1.098
	SQ7	3.664	1.110
	SQ8	3.573	0.984
	SQ9	2.884	1.410
	AVG_SQ	3.525	1.103
Information Quality (IQ)	**IQ1**	3.686	0.716
	IQ2	3.522	0.838
	IQ3	3.602	0.747
	IQ4	3.777	0.808
	IQ5	3.844	0.796
	IQ6	3.745	0.778
	AVG_IQ	3.696	0.781
Decision Quality (DQ)	**DQ1**	4.013	0.725
	DQ2	3.960	0.713
	DQ3	4.167	0.726
	DQ4	3.893	0.684
	AVG_DQ	4.008	0.712

**AVG_ [construct code] indicates the average construct value*

5.4 Structural equation modelling

Through Chapter 2 and Chapter 3, with a basis in the existing theoretical literature, the researcher detailed the structure of factors in relation to BI success variables and BI implementation factors. Firstly, the factor structure has a depiction of the initial aspect of the measurement model in relation to the implementation factors for BI consisting of a group of twelve constructs, namely the business plan and vision, management support, champions, resources, team skills, change management, data source systems, IT infrastructure, attitudes toward technology, trust and user participation. These constructs have been previously validated by numerous researchers (Arnott, 2008; Yeoh et al., 2008; Yeoh and Koronios, 2010; Woodside, 2011; Olszak and Ziemba, 2012; Anjariny and Zeki, 2013; Dawson and Van Belle, 2013; Sangar and Iahad, 2013; Puklavec et al., 2014; Grublješič and Jaklič, 2015; Nasab et al., 2015; Acheampong and Moyaid, 2016; Mesaros et al., 2016; Pham et al., 2016; Yeoh and Popovič, 2016; García and Pinzón, 2017; Lautenbach et al., 2017; Rezaie et al., 2017; Puklavec et al., 2017). The measurement model has a further group of three constructs—system quality, information quality and decision quality—that are the dependent variables. Further validation was needed in this research, as a protocol for these kinds of studies, prior to attempting to examine the relationships hypothesised between the independent and dependent variables. The model, therefore, has two construct sets: the BI implementation factors (twelve constructs) and the factors of BI success (three constructs). The relationships hypothesised between these two construct sets were developed in Chapter 3, based on the theory reviewed in Chapter 2. Therefore, to determine whether hypothesised relationships exist amongst the two construct sets, the model was tested as explained in the following two subsections. The analysis of the data within this study was carried out using the AMOS (v.25) software within a 2-step process in accordance with Hair et al. (2018). The first step involved validating the measurement model for the two construct sets through the use of CFA, while the second step involved the evaluation of the structural model along with the examination of the hypothesised relationships amongst the two construct sets through SEM.

5.4.1 Validation of the measurement model using confirmatory factor analysis

The technique of CFA enables the identification of relationships between observed indicators and unobserved variables (or latent constructs) through the provision of links between scores for the measurement of constructs (Hair et al., 2018). That, as well as the popularity in general of SEM, has led to a tendency for CFA to be employed instead of alternative approaches and techniques (Credé and Harms, 2015). Through the use of AMOS (v.25), this study undertook CFA to check the validity and the measurement model. This research adheres to the proposed two stages of Hair et al. (2018) for the assessment of CFA validity: goodness-of-fit indices and the construct validity. However, prior to the employment of the two stages, a test run was undertaken to improve the model. The procedures for improvement were applied based on criteria recommended in the literature. Kline (2015) asserted that the procedures for model refinement are needed in order for improvement and re-specification of the model to enhance the discriminant validity and achieve a better model fit. For Argyrous (2011), model improvement may be undertaken through the relation of indicators to different factors or through the dropping of them, and through the use of measurement errors that are correlated, or the relation of indicators to multiple factors. Furthermore, checking the modification indices (MIs), the standardised residuals and the searches of specification may help to improve the goodness of the fit of the model (Hair et al., 2018). As such, the improvement of the model was based on four criteria. Firstly, there was retention of only those indicator variables with a standardised regression weight over 0.50 (Hair et al., 2018). Secondly, in accordance with the work of Hair et al. (2018), those indicator variables with squared multiple correlations lower than 0.30 should be dropped. Thirdly, indicator variables that have high MI serve as a basis by indicating that variables are cross-loaded upon other constructs (Byrne, 2016). In that regard, a commonly used practice is to correlate parameter errors that form part of that factor (Hair et al., 2018). Furthermore, parameters showing high covariance between the errors they have whilst simultaneously having high regression weights are deletion candidates (Hair et al., 2018). Fourthly, indicator variables that have high values for standardised residual covariance that are over the minimum absolute value recommendation of 2.58 should be deleted (Hair et al., 2018). As such, there was a test run of the model, with the results shown in Appendix

5. First, close inspection of the standardised regression weight showed that the factor loading for two variables, SQ9 at 0.430 and TS4 at 0.469, were at values below the cut-off point of 0.5, and so it was decided to delete them from the model (see Figure 5.6). Second, inspection of the squared multiple correlations showed that all of the values were more than the 0.3 threshold recommended, other than SQ9 at 0.185 and TS4 at 0.220, with the decision made to delete these two items (see Appendix 5 and Figure 5.8). Thirdly, there was checking of the highest MI values in order to discover if there could be a relationship between two items within the same constructs in order for the model fit to be modified. Consequently, relationships were determined between the following items: IQ2 and IQ3 (MI = 42.608), DQ1 and DQ3 (MI = 32.614), and SQ2 and SQ3 (MI = 49.158) (see Figure 5.8). Fourthly, there was provision of a first clue related to the improvement of the model through careful review of the standardised residual covariance matrix (see Appendix 5). That step revealed a relationship for negative residuals that was overestimated between SQ8 and DQ3 within the model, where the standardised residual was beyond the acceptable 2.560 threshold at a value of 2.750. With careful checking of the table came the suggestion that most of the observed DQ3 associations with other variables were overestimated, and so DQ3 was the best deletion option. For instance, the standardised residual for DQ3 was 2.650 with SQ7, 2.090 with SQ6 and 1.782 with ITI2. As such, due to the misfit to the model, the decision was made for DQ3 to be dropped from the measurement model (see Figure 5.8).

To summarise, the following modifications were carried out so that the model could be improved:

- The deletion of SQ9 and TS4 based on the standardised regression weight and analysis of squared multiple correlations.
- The covariance of six terms of error (i.e. e46 with e47, e42 with e43, and e37 with e38) with a basis in the analysis of MI.
- The deletion of DQ3 based on the standardised residual covariance.

After the proposed model was modified, it was ready for the assessment of validity founded upon the above two adopted stages.

5.4.1.1 Goodness-of-fit indices

The goodness-of-fit indices is a good model component between the matrix of the estimated population covariance and the matrix of the sample covariance (Tabachnick and Fidell, 2019). Indices of goodness of fit summarise the discrepancies between values anticipated through statistical models and the observed values (DeVellis, 2016). The application of several standards and indices for goodness of fit assesses the model's fitness (Tabachnick and Fidell, 2019). Moreover, the assessment of those standards and indices is based on the suggestions that follow: the GFI ought to be at least 0.80 (Etezadi-Amoli and Farhoomand, 1996), the AGFI at least 0.80 (Segars and Grover, 1993; Chin and Todd, 1995; Etezadi-Amoli and Farhoomand, 1996; Gefen, 2000), IFI and TLI (equivalent to the index of non-normed fit) must have a value of at least 0.95 (Hu and Bentler, 1999), the CFI ought to be at least 0.90 (Bentler and Bonett, 1980; Hoyle, 1995; Jiang and Klein, 1999), and the RMSEA should be below 0.08 for a fit to be considered good, and below 0.05 for a fit to be considered excellent (Browne and Cudeck, 1992).

Argyrous (2011) note that the RMSEA is employed in measuring the discrepancy per degree of freedom. DeVellis (2016) show that CFI has often been identified as a stable descriptive for the fit of a model. Furthermore, it is recommended that TLI, GFI and CFI are used for comparing the absolute fit for a particular model to the absolute fit of a model that is independent. Brown (2015) recommend that at least three tests for fitness should be applied in assessing the overall model fit. It was decided, however, to report more results of indices in order for the accuracy and reliability of the fit of the measurement model to be increased.

Estimation of the measurement model was carried out through the estimation techniques of maximum likelihood provided through AMOS (v.25). As Kline (2015) notes, the maximum likelihood serves to represent the underlying statistical principle beneath the derivation for the estimates of parameters; the estimates are those maximising the likelihood of the data being drawn from the parameter of the population. Within this research, the chi-squared (x^2) value equates to 2218.332, with the degrees of freedom at 1782 and a probability value of below 0.001. The tests for the p-value for the absolute model fit and chi-square (x^2), however, have over-sensitivity to the size of sample. This study, therefore, also employed x^2 over the degrees of freedom as it was considered to be a measurement that was adequate; it is recommended that x^2 over the degrees of freedom is in a range from 1 to 3 (Browne and Cudeck, 1992; Vandenberg and Lance, 2000), whilst the study ration meets the recommended level with a DF/CMIN score of 1.245. The indices for the fit of the measurement model show good overall model fits. The findings for the fits are as follows: GFI = 0.849, AGFI = 0.829, IFI = 0.972, TLI = 0.969, CFI = 0.972, and RMSEA = 0.026. The statistic of fit and the indices for the proposed measurement model are shown in Table 5.6 (also see the depiction of the measurement model in Figure 5.8).

Table 5-12 Overall GFIs for CFA

Test	Recommended values	Achieved values
Chi-square divided by degrees of freedom (x^2/df)	$1.0 < x^2 / df < 3.0$	1.245
Goodness-of-Fit Index (GFI)	≥ 0.80	0.849
Adjusted Goodness-of-Fit Index (AGFI)	≥ 0.80	0.829
Incremental Fit Index (IFI)	≥ 0.95	0.972
Tucker–Lewis Index (TLI)	≥ 0.95	0.969
Comparative Fit Index (CFI)	≥ 0.90	0.972
Root Mean Square Error of Approximation (RMSEA)	≤.08	0.026

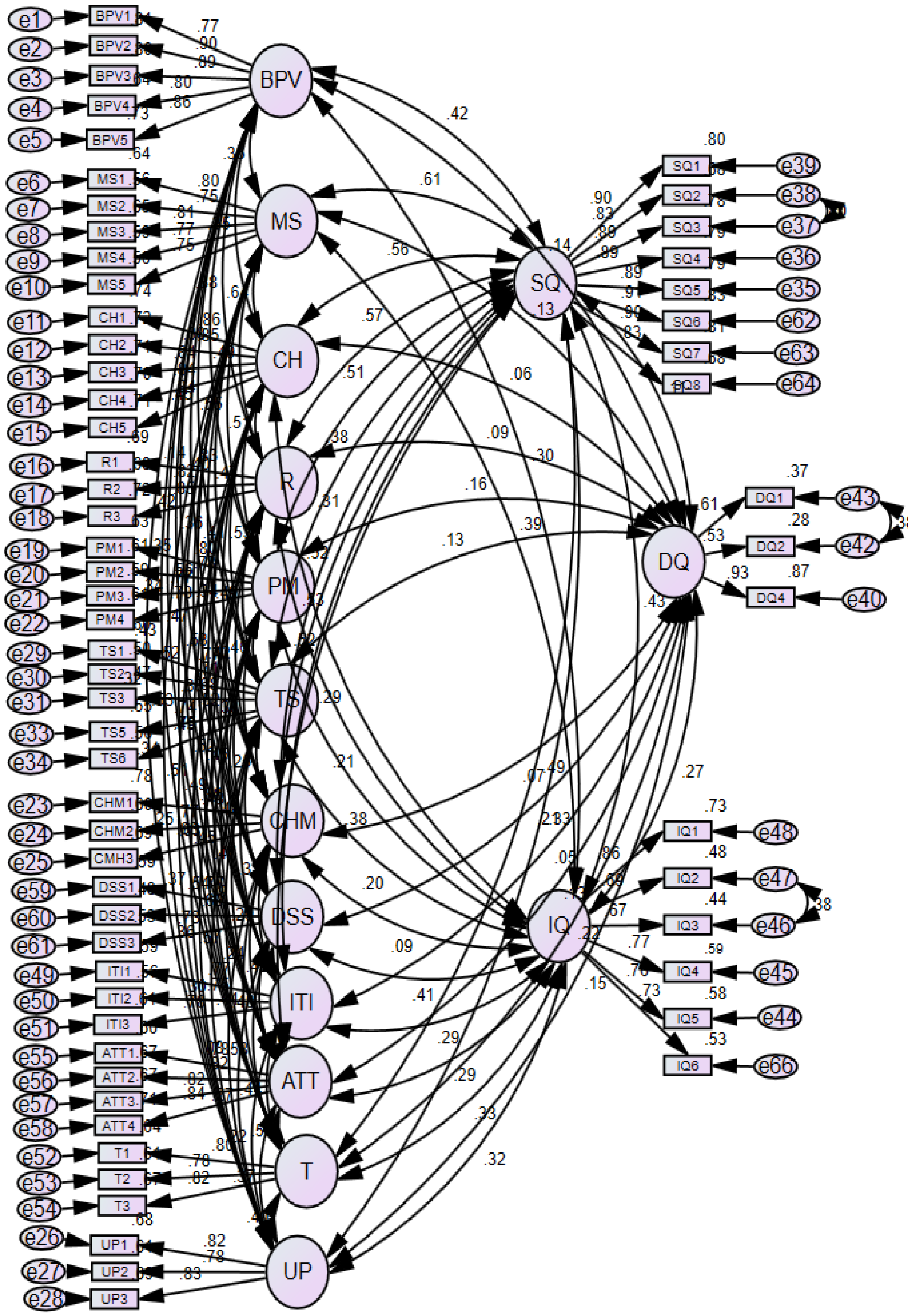

Figure 5.8 CFA output path diagram

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality

5.4.1.2 Construct validity

MacKenzie et al. (2011) correctly claim that within confirmatory research, a lack of validated measures leads to an increase in uncertainty, for no single study finding being able to be trusted. Numerous authors consider that uncertainty will tend to be proven to be inaccurate; however, without measure validation, uncertainty lingers on (MacKenzie et al., 2011). There are two primary components to construct validity: convergent validity and discriminant validity (Hair et al., 2018).

- **Convergent validity**

The term 'convergent validity' refers to the degree to which various measures, designed for testing the same construct, are in correlation with one another (DeVellis, 2016). Hair et al. (2018) also define convergent validity as the degree to which multiple measures are convergent upon a meaning that is consistent. Expressed in another way, the indicator ought to positively correlate to alternative indicators for the same construct of reflection (Hair et al., 2018). There are 15 constructs in the model, which all have multiple indictors, and so there is a need for testing for convergent validity. Three measures can be used to estimate convergent validity: composite reliability (CR), the average variance extracted (AVE) and standardised regression weight (factor loading). As can be seen in Table 5.7, three different cut-off values were used for the factor loading, the AVE and the CR of the measurement model (factor loading ought to be at least 0.5 and ideally have a value of 0.7 or over, AVE of greater than 0.5 shows that there is adequate convergence, and the CR ought to have a value of 0.7 or above).

Factor loading

High loadings on a factor show that there is convergence upon a latent construct. As a minimum, all of the factor loadings ought to have statistical significance. Nonetheless, even a loading that is significant may also have weakness. As such, the standardised regression weight ought to have a value of 0.5 or more and ideally be 0.7 or more. The factor loading for each of the constructs is shown in Table 5.7, where it can be seen that the factor loadings are high with values that are generally greater than 0.7, with none lower than 0.5. As such, the factor loading gave confirmation of convergent loading.

The average variance extracted

The AVE is a measure of the degree to which the variance captured by the latent variables within the structural equation models is shared amongst their measures. AVE can be calculated as the combined total of all the squared standardised factor loadings (the squared multiple correlations), which are then divided by the number of items. There is a general acceptance that items that return an AVE over 0.5 ought to be retained (Hair et al., 2018). This means that items that have an AVE of lower than 0.5 are not believed to have contributed to the internal consistency and, as such, were removed from this study. The results of the test for internal consistency are shown in Table 5.7, with the indication that all of the constructs have an AVE that is over 0.5. As such, convergent validity is strongly confirmed by AVE.

Composite reliability

Composite reliability (CR) or Construct reliability is a measure of internal consistency (Jarvis et al., 2003). The calculation of the measure is achieved through the factor loading squared sum per the yield of the construct from the model structural equation, and the summation of the terms of error variance for the constructs (Hair et al., 2018). Reliability ought to be 0.7 or above to show that there is an adequate degree of convergence or an adequate internal consistency (Hair et al., 2018; Tabachnick and Fidell, 2019). Table 5.7 shows the reliability of three constructs as being over 0.9, for ten constructs as being over 0.8, and for two constructs as being over than 0.7, which shows that there was a high level of construct reliability. High reliability of constructs reveals the existence of internal consistency and that the measures are consistent in their representation of the same latent kind of construct (Byrne, 2016).

Table 5-13 Convergent validity

Constructs	Item code	Factor loading	Composite reliability (CR)	Average variance extracted (AVE)
Business plan and vision (BPV)	**BPV1**	0.773	0.926	0.664
	BPV2	0.899		
	BPV3	0.892		
	BPV4	0.799		
	BPV5	0.857		
Management Support	**MS1**	0.800	0.882	0.600
	MS2	0.747		

(MS)	**MS3**	0.806		
	MS4	0.770		
	MS5	0.749		
Champion (CH)	**CH1**	0.859	0.926	0.714
	CH2	0.848		
	CH3	0.841		
	CH4	0.836		
	CH5	0.841		
Resources (R)	**R1**	0.832	0.874	0.697
	R2	0.822		
	R3	0.851		
Project Management (PM)	**PM1**	0.796	0.862	0.609
	PM2	0.780		
	PM3	0.768		
	PM4	0.778		
Team Skills (TS)	**TS1**	0.774	0.852	0.535
	TS2	0.710		
	TS3	0.684		
	TS5	0.739		
	TS6	0.746		
Change Management (CHM)	**CHM1**	0.881	0.867	0.685
	CHM2	0.771		
	CHM3	0.828		
Data Source Systems (DSS)	**DSS1**	0.767	0.774	0.533
	DSS2	0.691		
	DSS3	0.731		
Information Technology Infrastructure (ITI)	**ITI1**	0.771	0.809	0.586
	ITI2	0.746		
	ITI3	0.779		
Attitudes Toward Technology (ATT)	**ATT1**	0.777	0.888	0.664
	ATT2	0.816		
	ATT3	0.820		
	ATT4	0.845		
Trust (T)	**T1**	0.801	0.842	0.641
	T2	0.783		
	T3	0.817		
User Participation (UP)	**UP1**	0.824	0.854	0.661
	UP2	0.782		
	UP3	0.832		
System Quality (SQ)	**SQ1**	0.896	0.964	0.772
	SQ2	0.825		
	SQ3	0.886		
	SQ4	0.891		
	SQ5	0.889		
	SQ6	0.909		
	SQ7	0.902		
	SQ8	0.826		
Information Quality (IQ)	**IQ1**	0.855	0.883	0559
	IQ2	0.693		
	IQ3	0.667		
	IQ4	0.767		
	IQ5	0.760		
	IQ6	0.730		
Decision Quality (DQ)	**DQ1**	0.608	0.744	0.508
	DQ2	0.530		
	DQ4	0.934		

- **Discriminant validity**

The term ‘discriminant validity’ refers to the degree to which various constructs diverge from each other (Hair et al., 2018), or the degree to which measures have uniqueness and are not confounded by one another (Hair et al., 2018). Expressed another way, discriminant validity is the extent to which concepts that are conceptually similar have distinctiveness (Hair et al., 2018). Based on the work of Hair et al. (2018), there are two criteria employed in assessing discriminant validity: the indicator cross loadings (Hair et al., 2018), and the approach for assessment of discriminant validity that is more conservative than the cross loadings (Browne and Cudeck, 1992). The measurement of discriminant validity may be carried out through comparison of the average values of variance extracted for any two constructs with regard to the square estimate correlation for those constructs. There is good, significant discriminant validity for a construct if the square root for the AVE for the reflective constructs of multi-items is more than the absolute value for the correlations for the alternative constructs (Hair et al., 2018). Within this research, the discriminant validity was assessed through comparison of the square root values of AVE with the estimate of correlation between the constructs via the package of Gaskin statistical tools founded on the AMOS (v.25) analysis outputs (Gaskin, 2016). As shown in Table 5.8, the criterion is met by all the reflective constructs. The diagonal values that are shown in red and emboldened indicate that the AVE square root has a value that is higher than the estimate of the squared correlation for all other constructs. The results, therefore, suggest that the indicators share greater common variance with their corresponding constructs than to other constructs. The result is that, based on the criterion, the constructs are believed to be at a level that is significant, with discriminant validity that is good.

Table 5-14 Discriminant validity

	ATT	BPV	MS	CH	R	PM	CHM	UP	TS	SQ	DQ	IQ	ITI	T	DSS
ATT	**0.81**														
BPV	0.34	**0.85**													
MS	0.52	0.36	**0.77**												
CH	0.49	0.35	0.64	**0.85**											
R	0.49	0.38	0.49	0.51	**0.84**										
PM	0.45	0.38	0.55	0.47	0.54	**0.78**									
CHM	0.25	0.14	0.36	0.34	0.42	0.38	**0.83**								
UP	0.37	0.33	0.35	0.25	0.37	0.36	0.08	**0.81**							
TS	0.39	0.45	0.40	0.41	0.49	0.46	0.25	0.31	**0.73**						
SQ	0.52	0.42	0.61	0.56	0.57	0.51	0.31	0.33	0.38	**0.88**					
DQ	0.13	0.14	0.13	0.06	0.09	0.16	0.07	0.15	0.13	0.11	**0.71**				
IQ	0.29	0.30	0.39	0.29	0.21	0.38	0.09	0.32	0.20	0.43	0.27	**0.75**			
ITI	0.40	0.35	0.47	0.33	0.53	0.43	0.29	0.22	0.47	0.53	0.05	0.29	**0.77**		
T	0.55	0.43	0.53	0.51	0.63	0.54	0.44	0.40	0.57	0.49	0.22	0.33	0.44	**0.80**	
DSS	0.48	0.42	0.56	0.53	0.52	0.45	0.31	0.27	0.48	0.52	0.21	0.41	0.49	0.58	**0.73**

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality

5.4.1.3 Common method bias

There may be the occurrence of common method bias if the criterion and predictor variables are given by a rater or common source (Archimi et al., 2018). The common method bias can be tested in two ways: factor analysis's variance ratio and Harmon's one-factor test (Podsakoff et al., 2003). For this study, the testing of common method variance was through the factor analysis variance ratio (Podsakoff et al., 2003); there is determination of the ratio based on the condition that only a single factor exists within the result of the factor analysis, and that just one factor accounts for most of the variance amongst variables Podsakoff et al., 2003; Siemsen et al., 2010; Archimi et al., 2018). The result of the factor analysis using SPSS (v.25) indicates that the principal factor variance ratio, at a value of 29.109%, with total variance at a level of 64.764%, equates to 44.946% (i.e. lower than the 50.0% threshold) (see Table 5.9). The conclusion can be made, therefore, that common method bias does not exist within this research.

Table 5-15 Common method bias

Factor	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	19.535	29.598	29.598	19.212	**29.109**	29.109
2	3.752	5.685	35.284	3.378	5.119	34.228
3	3.446	5.221	40.505	3.130	4.743	38.971
4	2.740	4.151	44.656	2.442	3.700	42.671
5	2.337	3.541	48.197	2.034	3.082	45.752
6	2.185	3.310	51.507	1.867	2.828	48.580
7	2.133	3.232	54.739	1.733	2.626	51.206
8	1.988	3.012	57.752	1.610	2.440	53.646
9	1.782	2.700	60.452	1.441	2.184	55.830
10	1.631	2.471	62.923	1.278	1.937	57.767
11	1.579	2.392	65.314	1.217	1.845	59.611
12	1.437	2.178	67.492	1.074	1.627	61.238
13	1.274	1.930	69.422	.898	1.361	62.599
14	1.130	1.713	71.134	.755	1.144	63.743
15	1.071	1.623	72.757	.674	1.021	**64.764**
16	.939	1.422	74.179			
17	.836	1.267	75.446			
18	.734	1.113	76.559			
19	.699	1.059	77.618			
20	.647	.980	78.598			

5.4.2 The structural model utilising structural equation modelling

Once the fit of the measurement model had been established and assessment of the construct validity completed, the subsequent phase was the testing of the structural model. The specification of the structural model forms a step that is very significant for SEM, since the measurement model is converted to a model that is structural with the assignment of relationships from one construct to another based on the theoretical model proposed (Hair et al., 2018).

Within this study, the structural model (see Figure 5.9) is a representation of the full model that partly shows the structural connection among the latent. Whilst hypotheses within this study involve both indirect and direct effects, within the structural model there is the depiction of only the direct casual effects. The fit of the model has to be estimated, however, whenever there is modification of the model. With the structural model, there can only be correlation of the latent variables that are exogenous, and there may be covariance of the disturbances if their latent endogenous constructs do not predict one another (i.e. an arrow that is single headed does not directly link them). Thus, to facilitate easy presentation and illustration, all the paths of correlation between the endogenous constructs have been removed within Figure 5.9. Furthermore, causal paths that travel from one construct to another may be added without the testing of such paths in the achievement of a reasonable model fit; however, there is examination of all of the causal paths within this study. There is illustration in the structural model of the effects (and/or relationships) between the latent model variables and the primary hypotheses that are assessed later through the use of that same model (Hair et al., 2018). For the analysis of SEM, there is a need for the specification and identification of a structural model before the indirect and direct causal effects of the model are tested (Kline, 2015).

As Figure 5.9 shows, three endogenous latent constructs are included in the structural model: system quality, information quality and decision quality. Moreover, twelve exogenous latent constructs are included in the structural model: business plan and vision, management support, champions, resources, project management, team skills, change management, data source systems, IT infrastructure, attitudes toward technology, trust and user participation. Each of the endogenous latent constructs is composed of their relative items of measurement (indicators), which include their errors in measurement as the model depicts. As well as the latent constructs (twelve exogenous and three endogenous) within the model, there are 66 latent variables, including 63 terms of error and 3 disturbances, that were attached to all 63 indicators and endogenous constructs, respectively.

The inclusion of residuals or disturbances within the model allows it to give account for the potential effects from omitted causes because of interference from external construct(s) within the model. As Byrne (2016) notes, the residuals (latent variables) show the likely errors (discrepancies) within the prediction of endogenous constructs from those that are exogenous within the model. So that the hypothesised structural model can be evaluated, there was use of GFIs and other estimates of parameter.

Table 5.10 shows the findings from the goodness of fit having run SEM through AMOS (v.25) in order to demonstrate an adequate fitness level. The findings for the finalised structural model reveal a level of x^2 (chi-square) at 2231.367, with degrees of freedom (df) at a level of 1794, and a level of significance (p) at less than 0.005, which indicates a chi-square that is acceptable with the degrees of freedom (DF/CMIN) at a level of 1.244 in a range from 1 to 3 (Browne and Cudeck, 1992; Vandenberg and Lance, 2000). The other measurements for goodness of fit lie within the values recommended that are associated with good fit, namely, the GFI equated to 0.848, the AGFI was at 0.829, the IFI was 0.972, the TLI and the CFI equated to 0.972, with RMSEA equating to 0.026. The conclusion may thus be drawn that the structural model has consistency with the data from the sample, explained underlying constructs adequately, and is therefore suitable for the testing of the hypotheses. With the structural model's acceptability having been confirmed in the explanation of relationships between constructs, the following analytical stage involved the testing of each of the hypotheses for indirect and direct effects within the hypothesised model.

Table 5-16 Overall fit indices: hypothesised structural model

Test	Recommended value	Achieved value
Chi-square divided by degrees of freedom (x^2/df)	$1.0 < x^2 / df < 3.0$	1.244
Goodness-of-Fit index (GFI)	≥ 0.80	0.848
Adjusted Goodness-of-Fit Index (AGFI)	≥ 0.80	0.829
Incremental Fit Index (IFI)	≥ 0.95	0.972
Tucker–Lewis Index (TLI)	≥ 0.95	0.969
Comparative Fit Index (CFI)	≥ 0.90	0.972
Root Mean Square Error of Approximation (RMSEA)	≤.08	0.026

5.4.2.1 Hypotheses testing

Once the measurement model had been established and confirmed through the use of the statistics for the goodness of fit, the following step was the evaluation of the model and the testing of the hypotheses of the research through the structural model. The structural model defines relationships between the constructs or the latent variables, specifying which of the latent variables indirectly or directly impact on changes to the values of the other latent variables within the model (Byrne, 2016). The estimates for parameter were utilised for the creation of the matrix to estimate the population covariance for the structural model. Sixty-three items of measurement were used to identify the fifteen latent constructs. For the testing of the structural model, there was application of the covariance matrix amongst constructs. When the C.R./t-value (critical ratio) is greater than 1.96 in relation to an estimate (weight of regression), the value of the parameter coefficient has statistical significance at the significance levels of 0.001, at 0.01 and at 0.05 (Hair et al., 2018). There was acquisition of the C.R./t-value through division of the estimate for weight of regression by the estimate for the standard error (S.E.). The regression weight estimate, the standard error, standardised regression weights (β), critical ratio and statistical significance are shown in Table 5.11.

Table 5-17 Path coefficient weights for the structural model

Hypothesised paths			Estimate	S.E.	(β)	C.R./t-value	P
BPV	→	**SQ**	0.147	0.064	0.109	2.279	**0.023***
MS	→	**SQ**	0.223	0.078	0.190	2.855	**0.004****
CH	→	**SQ**	0.168	0.056	0.177	2.986	**0.003****
R	→	**SQ**	0.169	0.066	0.168	2.564	**0.010****
PM	→	**SQ**	0.103	0.08	0.075	1.288	0.198
TS	→	**SQ**	-0.12	0.082	-0.085	-1.46	0.144
CHM	→	**SQ**	0.007	0.047	0.007	0.139	0.889
DSS	→	**SQ**	0.079	0.092	0.057	0.861	0.389
ITI	→	**SQ**	0.274	0.083	0.198	3.309	***
ATT	→	**SQ**	0.158	0.066	0.131	2.374	**0.018***
T	→	**SQ**	-0.077	0.091	-0.062	-0.845	0.398
UP	→	**SQ**	0.045	0.052	0.042	0.865	0.387
BPV	→	**IQ**	0.059	0.052	0.071	1.147	0.251
MS	→	**IQ**	0.052	0.063	0.071	0.827	0.408
CH	→	**IQ**	-0.019	0.045	-0.033	-0.424	0.671
R	→	**IQ**	-0.162	0.054	-0.258	-3.015	**0.003****
PM	→	**IQ**	0.16	0.064	0.187	2.487	**0.013***
TS	→	**IQ**	-0.111	0.066	-0.126	-1.671	0.095
CHM	→	**IQ**	-0.053	0.038	-0.088	-1.4	0.162
DSS	→	**IQ**	0.215	0.075	0.25	2.888	**0.004****
ITI	→	**IQ**	0.053	0.067	0.062	0.794	0.427
ATT	→	**IQ**	-0.026	0.053	-0.035	-0.485	0.627
T	→	**IQ**	0.088	0.073	0.115	1.212	0.226
UP	→	**IQ**	0.106	0.042	0.159	2.521	**0.012***
SQ	→	**IQ**	0.155	0.048	0.249	3.243	**0.001*****
IQ	→	**DQ**	0.217	0.066	0.289	3.306	***
SQ	→	**DQ**	-0.006	0.03	-0.012	-0.188	0.851

- **Significance level:** * p=0.05; ** p=0.01; *** p=0.001

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality

R^2 (squared multiple correlations) for the constructs of an endogenous kind are shown within Table 5.12, with R^2 a statistical measure for how well real data points are approximated by a line of regression and a descriptive measure that lies between 0 and 1, to show how well one term predicts another one (Brown, 2015; Hair et al., 2018). Expressed another way, the closer the R^2 value is to 1, the greater the model's ability to predict a trend (Brown, 2015). The results for R^2 in this study suggest that the indicators within the study explain merely 28.1% of the decision quality's variability, 33.2% of the information quality's variability, and 55.2% of the system quality's variability.

Table 5-18 Squared multiple correlations for endogenous factors

Construct	**Squared multiple correlation (R^2)**
System Quality	0.552
Information Quality	0.332
Decision Quality	0.281

The path diagram for the constructs and the standardised regression weight are shown in Figure 5.9 below. Through the use of path estimates, there was examination of 27 hypotheses within this research, with sixteen of them rejected and eleven of them accepted (see Table 5.11 for the acceptance of a hypothesis, where there ought to be a positive and significant relationship of the independent variables to the dependent variables).

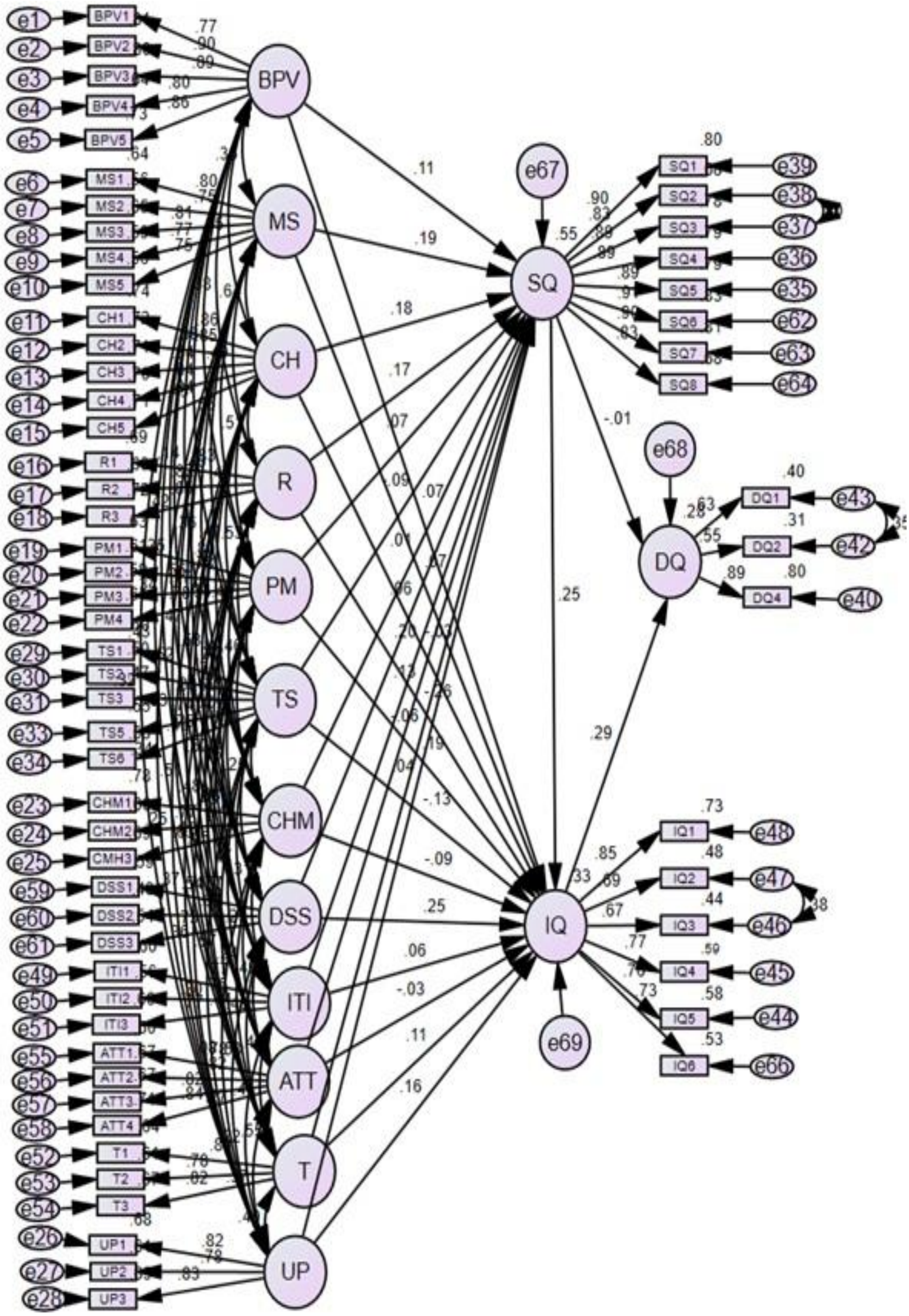

Figure 5.9 Path coefficients for the structural model

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality

The descriptions that follow present the hypotheses testing results in relation to Table 5.11.

Hypothesis H1a: *Business plan and vision have a positive effect on system quality*

The findings indicate the path estimate significance (t-value = 2.279; β = 0.109; P = 0.023) between system quality and the business plan and vision. Therefore, there is acceptance of hypothesis H1a since there is a direct, positive impact on system quality from the business plan and vision.

Hypothesis H1b: *Business plan and vision have a positive effect on information quality*

The findings indicate the path estimate insignificance (β = 0.071; t-value = 1.147; P = 0.251) between information quality and the business plan and vision. Therefore, hypothesis H1b is rejected.

Hypothesis H2a: *Management support has a positive effect on system quality*

The findings indicate the path estimate significance (β = 0.190; t-value = 2.855; P = 0.004) between system quality and management support. Therefore, there is acceptance of hypothesis H2a since there is a direct, positive impact on system quality from management support.

Hypothesis H2b: *Management support has a positive effect on information quality*

The findings indicate the path estimate significance (β = 0.071; t-value = 1.147; P = 0.827) between information quality and management support. Therefore, hypothesis H2b is rejected.

Hypothesis H3a*: Champions have a positive effect on system quality*

The findings indicate the path estimate significance (β = 0.177; t-value = 2.986; P = 0.003) between system quality and champions. Therefore, there is acceptance of hypothesis H3a since there is a direct, positive impact on system quality from champions.

Hypothesis H3b: *Champions have a positive effect on information quality*

The findings indicate the path estimate insignificance (β = -0.033; t-value = -0.424; P = 0.671) between information quality and champion. Therefore, hypothesis H3b is rejected.

Hypothesis H4a: *Resources have a positive effect on system quality*

The findings indicate the path estimate significance (β = 0.168; t-value = 2.564; P = 0.01) between system quality and resources. Therefore, there is acceptance of hypothesis H4a since there is a direct, positive impact on system quality from resources.

Hypothesis H4b: *Resources have a positive effect on information quality*

The findings indicate the path estimate significance (β = -.033; t-value = -3.015; P = 0.003) between information quality and resources. Therefore, there is acceptance of hypothesis H4b since there is a direct, negative impact on information quality from resources. (If there were an increase in resources then there would be a decrease in information quality, and a rejection of H4b.)

Hypothesis H5a: *Project management has a positive effect on system quality*

The findings indicate the path estimate significance (β = 0.075; t-value = 1.288; P = 0.198) between system quality and project management. Therefore, hypothesis H4a is rejected.

Hypothesis H5b: *Project management has a positive effect on information quality*

The findings indicate the path estimate significance (β = 0.187; t-value = 2.487; P = 0.013) between information quality and project management. Therefore, there is acceptance of hypothesis H5b since there is a direct, positive impact on information quality from project management.

Hypothesis H6a: *Team skills have a positive effect on system quality*

The findings indicate the path estimate insignificance (β = -0.085; t-value = -1.46; P= 0.144) between system quality and team skills. Therefore, hypothesis H5a is rejected.

Hypothesis H6b: *Team skills have a positive effect on information quality*

The findings indicate the path estimate insignificance (β = -0.126; t-value = -1.671; P = 0.095) between information quality and team skills. Therefore, hypothesis H6b is rejected.

Hypothesis H7a: *Change management has a positive effect on system quality*

The findings indicate the path estimate insignificance (β = 0.007; t-value = 0.139; P = 0.889) between system quality and change management. Therefore, hypothesis H6a is rejected.

Hypothesis H7b: *Change management has a positive effect on information quality*

The findings indicate the path estimate insignificance (β = -0.088; t-value = -1.4; P = 0.162) between information quality and change management. Therefore, hypothesis H7b is rejected.

Hypothesis H8a: *Data source systems have a positive effect on system quality*

The findings indicate the path estimate insignificance (β = 0.092; t-value = 0.057; P = 0.861) between system quality and data source systems. Therefore, hypothesis H7a is rejected.

Hypothesis H8b: *Data source systems have a positive effect on information quality*

The findings indicate the path estimate significance (β = 0.187; t-value = 2.487; P = 0.013) between information quality and data source systems. Therefore, there is acceptance of hypothesis H8b since there is a direct, positive impact on information quality from data source systems.

Hypothesis H9a: *IT infrastructure has a positive effect on system quality*

The findings indicate the path estimate significance ($\beta = 0.198$; t-value= 3.309; $P < 0.001$) between system quality and IT infrastructure. Therefore, there is acceptance of hypothesis H9a since there is a direct, positive impact on system quality from IT infrastructure.

Hypothesis H9b: *IT infrastructure has a positive effect on information quality*

The findings indicate the path estimate insignificance ($\beta = 0.062$; t-value = 0.794; $P = 0.427$) between information quality and IT infrastructure. Therefore, hypothesis H9b is rejected.

Hypothesis H10a: *Attitudes toward technology have a positive effect on system quality*

The findings indicate the path estimate insignificance ($\beta = 0.131$; t-value = 2.374; $P = 0.018$) between system quality and attitudes toward technology. Therefore, there is acceptance of hypothesis H10a since there is a direct, positive impact on system quality from attitudes toward technology.

Hypothesis H10b: *Attitudes toward technology have a positive effect on information quality*

The findings indicate the path estimate insignificance ($\beta = -0.035$; t-value = -0.485; $P = 0.627$) between information quality and attitudes toward technology. Therefore, hypothesis H10b is rejected.

Hypothesis H11a: *Trust has a positive effect on system quality*

The findings indicate the path estimate insignificance ($\beta = -0.062$; t-value = -0.865; $P = 0.398$) between system quality and trust. Therefore, hypothesis H11a is rejected.

Hypothesis H11b: *Trust has a positive effect on information quality*

The findings indicate the path estimate insignificance ($\beta = 0.115$; t-value = 1.212; $P = 0.226$) between information quality and trust. Therefore, hypothesis H11b is rejected.

Hypothesis H12a: *User participation has a positive effect on system quality*

The findings indicate the path estimate insignificance (β = 0.071; t-value = 0.865; P = 0.387) between system quality and user participation. Therefore, hypothesis H12a is rejected.

Hypothesis H12b: *User participation has a positive effect on information quality*

The findings indicate the path estimate significance (β = 0.159; t-value = 2.521; P = 0.012) between information quality and user participation. Therefore, there is acceptance of hypothesis H12b since there is a direct, positive impact on information quality from user participation.

Hypothesis H13: *System quality has a positive effect on information quality*

The findings indicate the path estimate significance (β = 0.249; t-value = 3.243; P = 0.001) between information quality and system quality. Therefore, there is acceptance of hypothesis H13 since there is a direct, positive impact on information quality from system quality.

Hypothesis H14: *Information quality has a positive effect on decision quality*

The findings indicate the path estimate significance (β = 0.289; t-value = 3.306; P< 0.001) between decision quality and information quality. Therefore, there is acceptance of hypothesis H14 since there is a direct, positive impact on decision quality from information quality.

Hypothesis H15: *System quality has a positive effect on decision quality*
The findings indicate the path estimate insignificance (β = -0.012; t-value = -0.188; P = 0.851) between decision quality and system quality. Therefore, hypothesis H15 is rejected.

To summarise, Figure 5.10 below show sthe final research model of all the significant regression paths and the accepted hypotheses, where all the insignificant regression paths, including the change management, trust and team skills constructs, are excluded from the model because of their aforementioned ineffectual impact. Moreover, Table 5.19 shows the result of the accepted and rejected hypotheses for this study

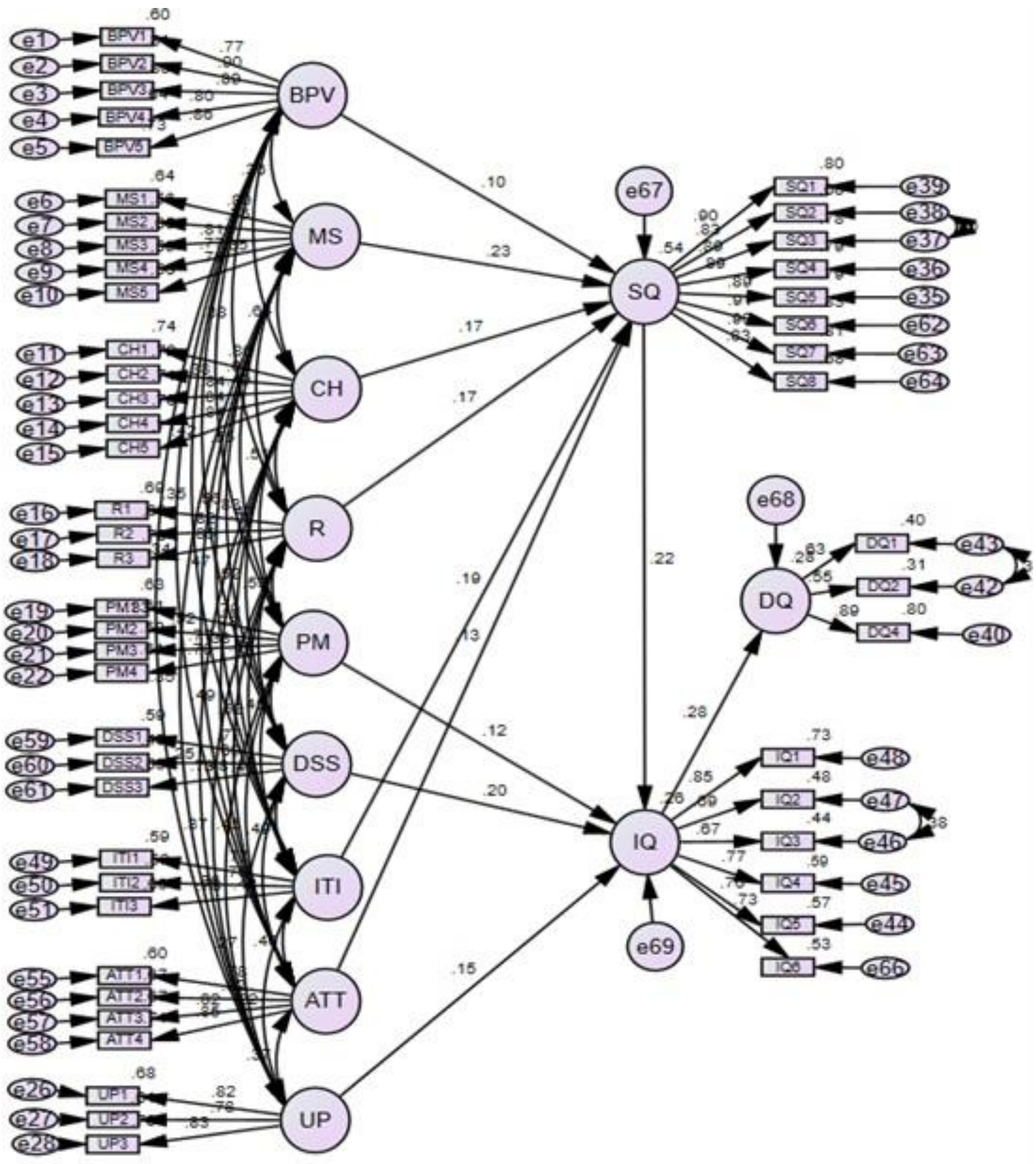

Figure 5.10 Research model with all the significant relationships based on SEM analysis

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality

Table 5-19: Summary of the hypotheses results

No.	Hypothesis	Result
H1a	Business plan and vision have a positive effect on system quality	Supported
H1b	Business plan and vision have a positive effect on information quality	Not supported
H2a	Management support has a positive effect on system quality	Supported
H2b	Management support has a positive effect on information quality	Not supported
H3a	Champions have a positive effect on system quality	Supported
H3b	Champions have a positive effect on information quality	Not supported
H4a	Resources have a positive effect on system quality	Supported
H4b	Resources have a positive effect on information quality	Not Supported
H5a	Project management has a positive effect on system quality	Not supported
H5b	Project management has a positive effect on information quality	Supported
H6a	Team skills have a positive effect on system quality	Not supported
H6b	Team skills have a positive effect on information quality	Not supported
H7a	Change management has a positive effect on system quality	Not supported
H7b	Change management has a positive effect on information quality	Not supported
H8a	Data source systems have a positive effect on system quality	Not supported
H8b	Data source systems have a positive effect on information quality	Supported
H9a	IT infrastructure has a positive effect on system quality	Supported
H9b	IT infrastructure has a positive effect on information quality	Not supported
H10a	Attitudes toward technology have a positive effect on system quality	Supported
H10b	Attitudes toward technology have a positive effect on information quality	Not supported
H11a	Trust has a positive effect on system quality	Not supported
H11b	Trust has a positive effect on information quality	Not supported

H12a	User participation has a positive effect on system quality	Not supported
H12b	User participation has a positive effect on information quality	Supported
H13	System quality has a positive effect on information quality	Supported
H14	Information quality has a positive effect on decision quality	Supported
H15	System quality has a positive effect on decision quality	Not supported

Furthermore, as shown in Table 5.13 below, the overall goodness of fit for the final research model was improved due to the exclusion of insignificant paths of regression.

Table 5-20 Overall fit indices: the final research model

Test	Recommended values	Achieved values
Chi-square divided by degrees of freedom (x^2/df)	$1.0 < x^2 / df < 3.0$	1.259
Goodness-of-Fit Index (GFI)	≥ 0.80	0.867
Adjusted Goodness-of-Fit Index (AGFI)	≥ 0.80	0.851
Incremental Fit Index (IFI)	≥ 0.95	0.976
Tucker–Lewis Index (TLI)	≥ 0.95	0.974
Comparative Fit Index (CFI)	≥ 0.90	0.976
Root Mean Square Error of Approximation (RMSEA)	≤.08	0.026

5.4.2.2 Mediation assessment

Mediation assessment is employed in estimating the paths by which a dependent variable is affected by an independent variable (Hayes, 2009), whereby the influence from an independent variable is carried to a dependent variable by a mediator (MacKinnon et al., 2012; Preacher, 2015). As Mathieu and Taylor (2006) note, there is the existence of full mediation when the direct effect between a dependent variable and independent variable, prior to the addition of the mediator, is one that is direct and statistically significant with a kind of mediation that does not have statistical significance, and when the indirect effect between the dependent and independent variables has statistical significance. Mathieu and Taylor (2006) note the existence of partial mediation if the direct effect (without or with mediation) between the dependent and independent variables has statistical significance and the indirect effect on the dependent variable from the independent one has statistical significance. Meanwhile, there is the existence of an indirect effect if the direct effect (without or with mediation) does not have significance and the independent variable’s indirect effect on the dependent variable has statistical significance (Mathieu and Taylor, 2006; MacKinnon and Pirlott, 2015). Through the use of the AMOS (v.25) software, the mediation form of analysis was conducted through the direct and indirect functionality founded on the approach of ‘bootstrapping’ of 1,000 procedures of resampling. The approach of bootstrapping with confidence intervals of 95% bias correction delivers since no normality assumption is made with regard to the distribution shape, particularly if primary data is available for the analyses (Mathieu and Taylor, 2006; Hayes, 2009; MacKinnon and Pirlott, 2015). Table 5.14 presents the analyses for the direct effect that is without mediation, the direct effect with mediation and the indirect effect.

Table 5-21 Mediation results

Indirect path	Direct effect without mediation	Direct effect with mediation	Indirect effect	Mediation type
	β (p-value)	β (p-value)	β (p-value)	
BPV → SQ → IQ	0.098 (0.114)	0.071 (0.173)	**0.027 (0.018)***	**Indirect effect**
MS → SQ → IQ	0.120 (0.165)	0.071 (0.308)	**0.047 (0.019)***	**Indirect effect**
CH → SQ →IQ	0.013 (0.867)	-0.033 (0.721)	**0.044 (0.004)****	**Indirect effect**
R → SQ → IQ	**-0.213 (0.013)***	**-0.258 (0.012)***	**0.042 (0.016)***	**Partial mediation**
PM → SQ → IQ	**0.207 (0.007)****	**0.187 (0.026)***	0.019 (0.171)	**No mediation**
TS → SQ → IQ	**-0.158 (0.037)***	-0.088 (0.156)	-0.021 (0.115)	**No mediation**
CHM → SQ → IQ	-0.088 (0.166)	0.159 (0.22)	0.002 (0.87)	**No mediation**
DSS → SQ → IQ	**0.270 (0.002)****	**-0.126 (0.012)***	0.014 (0.326)	**No mediation**
ITI → SQ → IQ	0.125 (0.104)	0.062 (0.419)	**0.049 (0.003)****	**Indirect effect**
ATT → SQ → IQ	-0.001 (0.992)	0.115 (0.722)	**0.033 (0.033)***	**Indirect effect**
T → SQ → IQ	0.088 (0.356)	-0.035 (0.263)	-0.015 (0.37)	**No mediation**
UP → SQ → IQ	**0.172 (0.007)****	**0.25 (0.027)***	0.011 (0.346)	**No mediation**
SQ → IQ → DQ	-0.006 (0.916)	-0.012 (0.821)	**0.072 (0.002)****	**Indirect effect**

- **Significance level**: * p=0.05; ** p=0.01; *** p=0.001

As Table 5.14 shows, the results of bootstrapping reveal that the indirect effects of the business plan and vision, management support, champions, IT infrastructure and attitudes toward technology constructs on the construct of information quality had significance. In addition, the results provide evidence of the dominating indirect effect that system quality had on the construct of decision quality. The suggestion from the results is that just the one construct of resources had partial effects of negative mediation upon information quality, with an indication that there was not full mediation with this model.

5.5 Chapter summary

Within this chapter, survey data was analysed through the use of statistical tools and the presentation of the findings. The survey was undertaken in order to examine the effects that factors in the implementation of BI had on the success of BI within the Jordanian mining sector. The findings of the survey were shown within several different sections, and: the techniques employed were introduced with explanations. This research utilised SPSS (v.25) and AMOS (v.25) for the analysis of the data. Once the data had been cleaned, analysis began with descriptions of the profile of the respondents and the descriptive statistics of the survey. Then, an assessment was carried out of the proposed measurement model based on the overall fit of the model, the validity of the construct and consideration for the common method bias. There was validation of the measurement model through the use of CFA and a number of statistical tests that included discriminant validity and convergent validity. This resulted in the development of scales that were both operationally and theoretically reliable and valid, and subsequent testing of the measurement model using those scales. Overall, upon finalisation, the scales were considered as possessing a satisfactory level of validity and so they were utilised for the purposes of testing the hypotheses. There was assessment of the structural model for the overall fit through the use of SEM, which was also employed to investigate the relationships between the independent variables for the implementation factors and the dependent variables for the success of BI. There was examination of the hypothesised structural model, with the 27 paths that represented the hypotheses (i.e. H1a, H1b, H2a, H2b, H3a, H3b, H4a, H4b, H5a, H5b, H6a, H6b, H7a, H7b, H8a, H8b, H9a, H9b, H10a, H10b, H11a, H11b, H12a, H12b, H13, H14, and H15). There was acceptance of eleven hypotheses (i.e. H1a, H2a, H3a, H4a, H5b, H8b H9a, H10a, H12b, H13, and H14), while 16 hypotheses were rejected (i.e. H1b, H2b, H3b, H4b, H5a, H6a, H6b, H7a, H7b, H8a, H9b, H10b, H11a, H11b, H12a, and H15). Furthermore, mediation analyses were undertaken in order to provide an overview of the potential indirect effect, partial mediation effect and full mediation effect. The findings revealed five indirect effects and one partial mediation, with no evidence of a full mediation effect. The following chapter presents a discussion of the findings acquired within this chapter so that the research question outlined in Chapter 1 can be answered.

Chapter Six:

Discussion

6.1 Introduction

This chapter features a discussion of the findings emerging from the hypotheses testing that were presented within Chapter 5, along with a comparison of those findings with the literature reviewed within Chapter 2 and Chapter 3. The findings are interpreted within this chapter to enable the thesis aim to be fulfilled, that is, for the advancement of knowledge and understanding of BI implementation, to acquire awareness of the factors that have an impact on such implementation, and to have an understanding of how BI impacts on decision-making quality within the mining sector in Jordan. This aim is achieved through meeting the five research objectives outlined within Chapter 1.

Chapter 6 is divided into four primary sections. Firstly, there is a presentation of the implementation factors for BI within the Jordanian mining sector in section 6.2. This is followed by a discussion of the findings related to the research hypotheses based on the conceptual model proposed for this research in section 6.3, which provides measurement of the impact that the implementation factors have on BI success. Within section 6.4, there is a discussion of the mediating impact from information quality and system quality. Following this, a discussion is presented regarding the revision and validation of the research framework in section 6.5. Finally, a chapter summary concludes the chapter.

6.2 The implementation factors in the mining sector of Jordan

In order to address the second research objective, namely, assessing the BI implementation factors in the Jordanian mining sector**,** this section illustrates and evaluates the findings that reflect the implementation factors adopted within the sector. Different suggestions emerged from the literature in relation to BI implementation factors, while there has been differing evaluations of those factors, and thus their significance levels vary between different organisations. In respect to implementation, rather than the achievement of organisational excellence, there is no equal focus by firms on every factor noted within the literature. The twelve key factors for implementation most commonly cited within the literature are: business plan and vision, management support, champions, resources, project management, team skills, change management, data source systems, IT infrastructure, attitudes toward technology, trust, and user participation. Descriptive findings for these factors are discussed within the subsections that follow.

- **Business plan and vision**

The business plan and vision are seen as an implementation success factor in BIS (Yeoh and Koronios, 2010; Sangar and Iahad, 2013; Pham et al., 2016; Yeoh and Popovič, 2016). Within this study, the definition of the business plan and vision is a project plan and objectives that are clear, in alignment with the strategies of the company, and where the activities cross-functionally involve integration. For the measurement of the business plan and vision, five items were employed. Firstly, the business plan and vision align with the company's mission, goals, objectives and strategies. Moreover, the business plan and vision contain quantified goals and objectives, as well as detailed action plans/strategies that support the company's direction. The business plan and vision are aligned with the company strategy, and contribute to the success of the company and the BI. In accordance with the findings presented in Table 5.5 (Section 5.3.2), this factor had an average mean score of 3.158 (i.e. above the midpoint of the scale), with the findings suggesting that the majority of the respondents believed there was alignment of the business plan and vision of the project for BI implementation with the strategies of the company, and that there were quantified and clear plan objectives. Furthermore, the findings show that there has been adoption of the business plan and vision during BI project implementation within the Jordanian mining sector. These results match those observed by Raghunathan (1992), Kearns and Sabherwal (2006), Arnott (2008), Dawson and Van Belle (2013), and Rezaie et al. (2017).

- **Management support**

Management support is one of the key factors for BI implementation, with numerous researchers stressing the significance of the role it plays (Yeoh and Koronios, 2010; Olszak and Ziemba, 2012; Anjariny and Zeki, 2013; Dawson and Van Belle, 2013; Puklavec et al., 2014; Mesaros et al., 2016; Pham et al., 2016; Yeoh and Popovič, 2016; García and Pinzón, 2017). Within this research, the measurement of management support was carried out in respect to encouragement for the utilisation of the system of BI and commitment to successful BI implementation. Furthermore, it involves being actively interested in those problems encountered with the BI and the provision of the resources necessary for the BI's implementation. Finally, it is noteworthy that user satisfaction has been a key management concern. In accordance with the findings shown in Table 5.5, this factor had an average mean score value of 3.27 (i.e. above the midpoint of the scale), which revealed that most of the respondents were receiving management support during the BI project implementation within the mining sector in Jordan. These findings are consistent with those in the literature concluded through the work of Wixom and Watson (2001), Hwang and Xu (2008) and Hasan et al. (2012).

- **Champion**

Many studies, such as those undertaken by Arnott (2008), Işık et al. (2013) and Boonsiritomachai et al. (2014), emphasise the role that project champions play as a precursor to successful innovation introduction, whereby the greater the advocacy level, the greater the likelihood that there will be successful adoption. The champion is defined by Heng et al. (1999) as a person who contributes to innovation through active and enthusiastic promotion of its progress during the vitally important stages of organisation. Champions have a keenness for experimenting with new ideas, are creative and have a willingness for taking risks that enables them to disregard the perceived restrictions to innovation. Within this study, the description of project champions is that they are leaders with the ability and power to encourage the project team in terms of the active and vigorous promotion of the company vision for the use of BI, manoeuvring the project past obstacles towards approval and implementation. In accordance with the findings in Table 5.5, this factor had an average mean score of 3.37 (i.e. above the midpoint of the scale The findings thus support the notion that project champions are important during BI project implementation within the Jordanian mining sector. Champions, therefore, provide active support and help in the promotion of a project through the creation of awareness, and the provision of political support, information and material resources, while playing an important role in the gaining of acceptance for the implementation of BI within companies. Project champions for the implementation of BI may be characterised through their encouragement for team working and their participation within the process of decision-making, as well as a willingness to listen with regard to problems encountered within implementation. Furthermore, a champion has concern for ensuring the project is completed successfully. The champion should hail from the area of ISs. The findings have consistency with regard to the research by Kayworth and Leidner (2001), Wixom and Watson (2001), Hwang and Xu (2008), and Owusu et al. (2017), thus suggesting that the project champion is a significant factor of implementation.

- **Resources**

The resources of the project are believed to be a factor of implementation for BI project success (Arnott, 2008; Yeoh et al., 2008; Acheampong and Moyaid, 2016; Mesaros et al., 2016; Yeoh and Popovič, 2016). Within this study, there was measurement of project resources in respect to whether there was adequate funding for the project with support from team members to achieve their tasks, and the implementation team being given sufficient time for the project implementation to be completed. In accordance with the findings in Table 5.5, the average mean score was 3.236 for this factor (i.e. above the midpoint of the scale), which suggests that the majority of the respondents believed that there was adequate funding of resources for the BI project, sufficient time for the completion of the process of implementation and support from human resources. Furthermore, the findings suggest that sufficient resources were offered during BI project implementation within the mining sector in Jordan. These findings are echoed in the literature, such as through the work of Hwang and Xu (2008), Işık et al. (2013) and, more recently, that of Hatta et al. (2017).

- **Project management**

The project management is an influencing factor on the success in BI implementation, whereby if project management is effective then there is further help to accomplish the project for implementation (Anjariny and Zeki, 2013; Pham et al., 2016; Rezaie et al., 2017). Typically, the infrastructure for project management is defined by the top management, along with their selection of the project management team members. The selection of members is good when there is a balance of technological and business knowledge within the team (Al-Mashari et al., 2003). In this study, the description of project management is a team with a willingness to assess the performance of the project within the early stages of implementation, with a responsibility for measuring performance in implementation and having control over the process, whilst being able to communicate clearly with the members of the implementation team. In accordance with the findings in Table 5.5, the average mean value for this factor was 3.326 (i.e. above the midpoint of the scale). The findings thus support the notion that the project management role is advanced by companies during the BI project implementation within the Jordanian mining sector. Moreover, there is involvement within the process of both the implementation team and the project management. Since both parties stress effective communication, it is inevitable that communication is a crucial factor in the implementation of the BIS. This conclusion has consistency with the literature that explored project management as a key implementation factor for supporting the success of BI projects within various contexts (Grover et al., 1995; Hwang and Xu, 2008).

- **Team skills**

Team skills have importance to the implementation of BI, since people are significant for the implementation of a system with a potentially direct impact on its failure or success. Therefore, the implementation of team skills has a key influence on project outcomes (Wixom and Watson, 2001; Yeoh and Koronios, 2010; Anjariny and Zeki, 2013; García and Pinzón, 2017). A project team ought to have members that hail from a range of business areas so that ideas can be shared and the potential for standardisation can be increased (Watson et al., 2002). Within this research, team skills include abilities that are both interpersonal and technical. If a team has strong technical skills, it is able to undertake its tasks effectively. Furthermore, interpersonal skills have importance since team members must work together to complete their respective tasks. The findings in Table 5.5 reveal that the average mean score for this factor was 3.47 (i.e. above the midpoint of the scale), which was the highest mean score and suggests that most of the respondents believed that the skills of the BI team were reasonable. Moreover, the findings suggest that team skills are a significant factor whilst BI projects are being implemented within the Jordanian mining sector. In regard to that factor, there was an aim of evaluating the skills of team members whilst BI was implemented, through ensuring that there were good interpersonal skills, and that project team members hailed from various areas of expertise and had the correct technical BI skills.

Furthermore, team member skills were complimentary to one another, with the team having various functional backgrounds and varied experience. These findings align with those of Xu and Hwang (2007), Mesaros et al. (2016) and Rezaie et al. (2017).

- **Change management**

It has been suggested that change management is significant for the successful implementation of BI, most notably by Sangar and Iahad (2013) and García and Pinzón (2017). The implementation of BI is seen as a change management project managed as an incremental form of change or transformation. An initial priority for top management within this kind of business scenario is to manage inertia within the organisation to the acceptance of change, and any associated conflicts (Al-Mudimigh et al., 2001). Within this study, change management is described as a process for the transformation of organisations and individuals to a desired state, through support given to the users and implementation team, and consultation to address problems encountered during the period of implementation. In accordance with the findings in Table 5.5, the average mean score for this factor of 2.68 (i.e. lower than the midpoint of the scale) shows that the majority of the respondents were of the view that the change management process was lacking in some regard during the implementation period of BI projects within the Jordanian mining sector. As Yeoh and Popovič (2016) note, if change management is insufficient it can cause the BI implementation process to be poorly understood. The findings emerging from this study do not, however, agree with the previous research in the literature (Grublješič and Jaklič, 2015; Rezaie et al., 2017).

- **Data source systems**

The systems of data source are a success factor that has a specific uniqueness with regard to the implementation of BI, representing the need for data to be integrated from a variety of source systems. If integration is to be successful, there is a dependency on the types and number of the source systems, their quality and data accuracy, and the ability of the BIS to extract the data required from all of those source systems (Wixom and Watson, 2001; Anjariny and Zeki, 2013; Dawson and Van Belle, 2013). Within this study, the description of the data source system is that it represents source system quality including readiness, standardisation and disparity in the provision of data to the system of BI. In accordance with the findings in Table 5.5, the average mean score was 3.3 for this factor (i.e. above the midpoint of the scale). The findings thus support the notion that an acceptable system of data source was provided by the company to the BIS during the BI project implementation within the mining sector in Jordan. There were disparate and diverse applications of data sources used, and therefore for the BI. These findings thus align with those from Wixom and Watson (2001), Arnott (2008), Hwang and Xu (2008) and Puklavec et al. (2017).

- **IT infrastructure**

The IT infrastructure was given consideration as an implementation factor for BI project success (Arnott, 2008; Yeoh and Koronios, 2010; Pham et al., 2016; García and Pinzón, 2017; Lautenbach et al., 2017). The infrastructure of IT has been defined as the available and integrated set of services of IT infrastructure for supporting new initiatives within firms, as well as existing applications (Weill et al., 2002). A firm’s IT infrastructure refers to the ability to provide information and data to users to appropriate degrees of timeliness, accuracy, security, confidentiality and reliability, while the infrastructure can be tailored to the emerging directions and needs of a business, and there is provision of universal connectivity, as well as access with sufficient range and reach (Fink et al., 2017). Within this research, the definition for IT infrastructure is that the company is capable of providing appropriate software, hardware and database and network technologies prior to the implementation of the BIS. In accordance with the findings in Table 5.5, the average mean score was 3.46 for this factor (i.e. above the midpoint of the scale), suggesting that most of the respondents believed there was suitable IT infrastructure during BI project implementation within the Jordanian mining sector. The result appears consistent with the findings of other research that found IT infrastructure to be a critical factor of implementation, conducted by Wixom and Watson (2001), Xu and Hwang (2007), Naderinejad et al. (2014) and Rezaie et al. (2017).

- **Attitudes toward technology**

The attitudes toward technology are thought to be a success factor for the implementation of an IS (Agrawal and Prasad, 1999; Aladwani, 2002; Chau and Hu, 2002). Attitudes toward technology were described by Petter et al. (2013) as the extent to which users have a favourable perspective of technology. Furthermore, IS implementation cannot be perceived as successful unless there are positive user attitudes toward technology that match their expectations (Al-Mashari, 2003). In accordance with the findings in Table 5.5, this factor had an average mean score of 3.4 (i.e. above the midpoint of the scale), which suggests that the majority of the respondents were in agreement with the importance of the factor items for implementation. The finding shows that the use of BI was viewed as being enjoyable, interesting and useful through the process of implementation. Furthermore, the findings suggest that the attitudes toward technology were a significant factor during the BI project implementation within the mining sector in Jordan. This study's findings align with those reported by Guimaraes et al. (1996) and Guimaraes and Igbaria (1997).

- **Trust**

Trust in the successful implementation of an IS has been suggested to be a key factor according to several researchers, most notably in the works of Gefen et al. (2003) and Wang and Emurian (2005). Trust has been defined as a willingness for reliance on a partner in whom one has sufficient confidence (Moorman, 1993), and is considered to be a significant factor for the relationship between computers and humans (Fogg and Tseng, 1999). In accordance with the findings in Table 5.5, the factor had an average mean score of 3.26 (i.e. above the midpoint of the scale), thus suggesting that most of the respondents had trust in the BIS, and that they held a favourable view of the technology and its applications. Moreover, the findings suggest that trust in the system of BI is a significant factor during BI project implementation within the Jordanian mining sector, where the findings align with studies by Zhang and Prybutok (2005), Lee et al. (2007) and Cyr et al. (2009).

- **User participation**

User participation (Wixom and Watson, 2001; Olszak and Ziemba, 2012; Dawson and Van Belle, 2013; Işık et al., 2013; García and Pinzón, 2017) was the final implementation factor explored in this study. Through user participation, it can be ensured that the requirements of users are captured accurately and communicated clearly for subsequent action by the project team. It has particular importance if the system requirements are initially unclear (Wixom and Watson, 2001). Furthermore, the means of managing expectations and the fulfilment of users' requirements are facilitated by user participation. When the system is used, people have a tendency to gain an enhanced understanding of its limitations and potential, and the likelihood of their acceptance of the system increases (Schieder and Gluchowski, 2011). In accordance with the findings in Table 5.5, the factor had an average mean score of 3.25 (i.e. above the midpoint of the scale), which suggests that most of the respondents participated and were involved in the BI project implementation in the Jordanian mining sector. Therefore, users feeling part of the process of development acquire a greater appreciation and understanding of the system of BI, as well as its application and capabilities. A consequence is that user involvement may help in the management of expectations which, in turn, leads to enhanced user intelligence solutions (Yeoh et al., 2008). The findings from this research align with the studies of Wixom and Watson (2001), Hwang and Xu (2008), Hasan et al. (2012), Mesaros et al. (2016) and Rezaie et al. (2017).

6.3 The impact of the implementation factors on business intelligence success

In order to address the third objective, that is, testing the impact of the implementation factors on BI success, hypotheses were developed based on the implementation factors' impact (i.e. business plan and vision, champions, management support, team skills, change management, resources, IT infrastructure, attitudes toward technology, trust, data source systems, and user participation), and to determine their impact on BI successas represented by system quality and information quality. Furthermore, the hypothesising was carried out in order to analyse BI success's impact on decision quality within the Jordanian mining sector context. The findings revealed that numerous hypotheses had acceptability within the context, whilst others did not (see Table 5.11). The sections that follow provide an examination of those mixed findings.

- **Impact of business plan and vision upon business intelligence success (H1a,b)**

Within hypothesis H1a, the proposal was made that the business plan and vision have a positive effect on system quality, with the study findings confirming that the business plan and vision did indeed have a positive impact on system quality. However, hypothesis H1b forwarded that there is a positive impact from the business plan and vision on information quality, which was not supported by the findings. The study findings have consistency with those in previous work undertaken by Arnott (2008), Dawson and Van Belle (2013) and Nasab et al. (2015). Within an investigation of 98 professionals of data warehousing and BI, Hwang and Xu (2008) showed that there was a relatively stronger impact from the business plan and vision on system quality than from the other BI implementation factors studied, although they argue that the business plan and vision does impact on the variable of information quality success. A significant relationship between both of the variables was found in a study undertaken by Pham et al. (2016), while Rezaie et al. (2017) also discovered a significant relationship between those two variables. The findings for this study show that the business plan and vision factor strongly predict the success of BI within the Jordanian mining sector, with the implication that high quality business with a realistic vision will tend towards successful BI implementation with an impact at the technical level, which relates to system quality. The findings related to hypothesis H1a confirm the significant impact of a clear business plan and vision on increasing BIS quality. Based on these findings, it may be stated that development of the BI project business plan and vision may play a significant role in BI success as there is a significant and direct impact on enhancing system quality.

- **Impact of management support on business intelligence success (H2a,b)**

Within this research, hypotheses were made of a direct positive impact from management support on system quality (H2a) and information quality (H2b). The data revealed a significant relationship between system quality and management support; however, management support was found to impact insignificantly on information quality, thus indicating agreement with previous studies, which means that management support has a direct influence on system quality/success at the technical level for the associated BIS. This finding confirms the results acquired in other research such as Anjariny and Zeki (2013), Dawson and Van Belle (2013) and Acheampong and Moyaid (2016), who all found that management support has a direct influence in that respect. In their empirical work, however, Xu and Hwang (2007) discovered that support from management does not impact on information quality. Moreover, support from management is expected to have a direct impact on the success of BI (García and Pinzón, 2017; Lautenbach et al., 2017). In general, the support of management for BI does promote quality in the specific system through facilitating the allocation of the resources required both during and after the BI project (Grublješič and Jaklič, 2015; Puklavec et al., 2017). Actions of motivation shown by senior level managers also make a contribution to the successful implementation of BI (Rezaie et al., 2017). The strength of the relationship between system quality and management support was discovered within this research to strongly reflect on the extent to which mining companies within Jordan support their employees through taking steps for development, enhancing communication and the motivation for using the system of BI. The findings in relation to hypothesis H1a confirm the fact that the influence from management support on increased BIS quality is significant. Based on the results, it may be stated that the promotion and development of management support may play a significant role in BI success as there is a significant and direct impact on increasing the system quality.

- **Impact of champions on business intelligence success (H3a,b)**

Within hypothesis H3a, the proposal was made that the project champion has a positive effect on system quality, with the study findings confirming that the project champion did indeed have a positive impact on system quality. Then, hypothesis

H1b proposed a positive effect on information quality from the project champion, but that hypothesis cannot be supported within the study context. Therefore, this study's findings align with those from previous research exploring the relationship between BI success and project champions. The work of Nasab et al. (2015) provides confirmation of a positive relationship between the system quality for BI and project champions, while in their study of organisations in Malaysia, Anjariny and Zeki (2013) also show project champions to be a strong predictor of BIS success. A strong relationship was discovered between BI success and project champions by Owusu et al. (2017). The project champion's role is critical for deriving consensus and for overseeing the whole implementation lifecycle. As Acheampong and Moyaid (2016) note, a project champion has the power to set goals and legitimatise change, as well as ensuring that those challenges encountered during implementation are suitably addressed (Jarvenpaa and Ives, 1991). Furthermore, the project champion's role is the promotion, support and driving of the respective project. In particular, the project champion provides support in political terms, facilitates the information flow in relation to the project, acquires the necessary project resources and overcomes any resistance that may be present in the organisation (Howell and Higgins, 1990). This study's findings reveal that the project champion has a clear impact on the BIS quality, a result that has consistency with previous research. The causes for that impact can be explained due to the authority and power held by the project champion within the mining sector of Jordan being of paramount significance to the effective implementation of programmes or systems. The project champion's role has to be established in the organisation in such a way that their influence and objectivity are pronounced. The finding in relation to hypothesis H3a thus provides confirmation that there is a significant influence from the project champion on BIS quality. It may be also be asserted that a significant role is played by the project champion in relation to BIS success, as there is a significant and direct influence on the BIS quality.

- **Impact of resources on business intelligence success (H4a,b)**

Within this research, hypotheses were made of a direct and positive impact of resources on system quality (H4a) and information quality (H4b). The data revealed a significant impact from the implementation factor of resources on BIS success through information quality and system quality. There is a negative regression path, however, between the dependent information quality variable and the independent predictor resources variable. Therefore, hypothesis H4b was not supported, with this finding being consistent with previous research that concluded that the allocation of resources for the project of BI has a direct impact on BIS success (Arnott, 2008; Boonsiritomachai et al., 2014; Acheampong and Moyaid, 2016). Likewise, Hatta et al. (2017) found that project resources are essential for successful implementation of BISs, while Owusu et al.'s (2017) Ghanian study discovered an influential relationship between project resources and the success of the BIS. Within a study in Iran, there was also substantiation of such a relationship in the work of Salmasi et al. (2016). Similarly, Rezaie et al. (2017) undertook work that offers support for the validity of this relationship. Hwang and Xu (2008) found a positive and direct influence of the resources of companies on system quality, although they did not reveal any impact on information quality. An important factor of implementation, therefore, is the availability of suitable resources. Traditional resources for projects include time, finance and people, and insufficiency of resourcing will have a negative impact (Herrmann, 2004; Eckerson, 2005). The results of this study reveal an influence from project resources on BIS quality, which is consistent with previous research. This finding means that the resources for the project are insufficient, and that a reliance on individual consultants and/or implementation partners does not have efficiency within the mining sector in Jordan, which if addressed could enhance the success of the company in terms of BIS implementation. This finding in relation to hypothesis H4b gives confirmation that the impact of project resources on BIS quality is a significant one. It may therefore be expressed that project resources play an important role within BIS success in the research context as there is a significant and direct influence on increasing BIS quality.

- **Impact of project management on business intelligence success (H5a,b)**

Within this research, hypotheses were made of a direct and positive impact from project management on system quality (H5a) and information quality (H5b). The data revealed that the relationship between system quality and project management is an insignificant one; however, project management was found to impact significantly on information quality. Therefore, the study findings align with those of previous investigations that suggest a strong relationship existing between increased BI success and project management (Yeoh and Koronios, 2010; Pham et al., 2016; Yeoh and Popovič, 2016). These findings are also in agreement with those of Anjariny and Zeki (2013) that showed the influence of project management on the level of success for the company in its BIS. Furthermore, in the case of dynamic project management with greater involvement comprehending IT, then there is an increased likelihood of the project management having an increased positive impact on the system of BI (Arnott, 2008). Hwang and Xu (2008) assert that increasing the understanding and awareness of benefits from project management during the implementation of BI could positively impact the information quality of the system of BI. The suggestion from the previous literature is that BI project management that controls and assesses the implementation of BI would tend to be associated with the success of the BI. The term ‘project management’ refers to the planning of the system implementation along with the acquisition of IS, the organisation and selection of an appropriate workforce, as well as administration and scrutiny/monitoring (Acheampong and Moya, 2016). Alternatively, Hahn et al. (2008) emphasises that project management is vital for the delivery of quality products. Given the intricate nation of BI implementation, Boonsiritomachai et al. (2014) recommend the need for proficiencies in project management as well as technological and change management. In conclusion, it may be stated that Jordanian mining companies note that project management has a significant impact on the information quality offered by the system of BI. The findings related to hypothesis H5b confirm that the impact from project management on increasing BIS information quality and data quality has significance. Based on the results, it may be asserted that enhanced project management and increasing activities such as assessment, control and communication whilst the BI is being implemented may play an important role in BI success through a significant and direct impact on improving information quality.

- **Impact of team skills on business intelligence success (H6a,b)**

Within this research, hypotheses were made of a direct and positive impact from team skills on system quality (H6a) and information quality (H6b). The findings revealed the existence of an insignificant relationship between BIS and information quality and team skills, which is partly consistent with two other studies. Hwang and Xu (2008) found team skills did not have an influence on system quality, although they argued that team skills affect the information quality provided from the BIS. A significant positive influence on BI success from team skills was not found by Hatta et al. (2017), which is inconsistent with a number of other investigations that show team skills to have importance within a variety of contexts for successful BI project implementation (Olszak and Ziemba, 2012; Anjariny and Zeki, 2013; Mesaros et al., 2016; García and Pinzón, 2017; Rezaie et al., 2017), where most of the cited studies show a strong and positive relationship between BIS success and team skills. The results of this study demonstrate that the relationship was insignificant in the direction predicted between team skills and success of BI. Those hypotheses, therefore, have no support from the survey of the mining sector within Jordan. Despite careful re-examination of the literature, these unexpected findings are surprising and thus there is a need for future research in order for possible explanations to be explored.

- **Impact of change management on business intelligence success (H7a,b)**

Within this research, hypotheses were forwarded of a direct and positive impact from change management on system quality (H7a) and information quality (H7b). The findings did not provide any confirmation of a relationship between BI success and change management, and they rejected the hypotheses of change management having a positive impact on system quality and information quality. This differs from the findings in the literature examining the direct impact of change management on BIS success (Yeoh et al., 2008; Yeoh and Koronios, 2010; Sangar and Iahad, 2013; Grublješič and Jaklič, 2015; García and Pinzón, 2017; Rezaie et al., 2017). These studies revealed a strong and positive relationship between BI success and change management, thus implying that information quality and BIS will be increased by change management. However, a statistically significant relationship in the direction predicted was not found in this study between information quality and BIS and change management, and therefore these hypotheses are not supported within the mining sector in Jordan. Detailed investigation of this unexpected result remains pertinent for future research, with several potential explanations that could be investigated; for example, a relatively low change management score within the survey population could have impacted on the significance of the relationship, since this suggests a lack of support from the consultants of change management in the resolution of problems during BI implementation in Jordanian mining companies. The emphasis, then, is that user participation and honest, consistent and open communication during each change management phase is thought by users to be important. Moreover, if unaddressed, then the intention may form to not use the system, leading to the non-adoption of the change. Such realities appear to have impacted on the findings related to hypothesis H7a and hypothesis H7b.

- **Impact of data source systems on business intelligence success (H8a,b)**

Within hypothesis H8a, the proposal was forwarded of a positive impact on system quality from the data source systems; however, within this study's context, the hypothesis cannot be supported. Meanwhile, hypothesis H8b proposed that data source systems have a positive influence on information quality, which can be positively supported within the study context. The study findings have consistency with previous works undertaken by Arnott (2008), Anjariny and Zeki (2013), Dawson and Van Belle (2013) and Grublješič and Jaklič (2015). Furthermore, Hwang and Xu (2008) discovered that the data source systems have significance with respect to BI information quality. The data source system was found by Işık et al. (2013) to be a significant implementation factor for BIS success within organisations in the United States. Meanwhile, Lautenbach et al. (2017) argue that there is a statistically insignificant relationship between BI success and data source systems amongst organisations in South Africa. Furthermore, Hasan et al. (2012) discovered no significant impact of data source systems on BI success in an Iranian organisation. The findings in relation to hypothesis 8b confirm that the impact from the data source system on IS has significance within the direction predicted, which is consistent with the literature (Dawson and Van Belle, 2013; Işık et al., 2013; García and Pinzón, 2017). Based on these results, it is apparent that the data source system may play a significant role in BIS success as it has a significant and direct impact on increased BIS success. The results, therefore, show that through the aforementioned mechanisms, the mining sector in Jordan ought to be capable of enhancing its existing strategies or approaches to BI implementation success through providing support for the necessary sources of external and internal data.

- **Impact of IT infrastructure on business intelligence success (H9a,b)**

Within this research, hypotheses were formed that IT infrastructure has a positive and direct impact on system quality (H9a) and information quality (H9b). The findings revealed a significant relationship between system quality and IT infrastructure, but an insignificant effect between information quality and IT infrastructure. This agrees with previous studies, underscoring a direct impact on the technical level of success of the BIS from IT infrastructure. The result provides confirmation of findings from a number of studies such as Arnott (2008), García and Pinzón (2017) and Lautenbach et al. (2017), who discovered that IT infrastructure impacts directly in that regard. However, in their empirical study, Xu and Hwang (2007) did not find an impact from IT infrastructure on system quality. A positive relationship was confirmed between technical implementation and IT infrastructure by Wixom and Watson's (2001) study. Within their investigation related to Iranian banking, Rezaie et al. (2017) also discovered that BI success is strongly predicted by IT infrastructure, with a strong relationship between BI success and IT infrastructure found by Salmasi et al. (2016). The relationship strength between system quality and IT infrastructure was found in this research to be a strong reflection of the extent to which mining companies in Jordan could focus on increasing their expenditure related to the operation and maintenance of IT infrastructure, comprising numerous integrated systems, with enhanced BIS quality as a result. The findings related to hypothesis H9a provide confirmation that the impact from IT infrastructure on increasing the BIS quality is significant. Based on the results, it can be asserted that the promotion and development of IT infrastructure may play an important role in BI success as it has a significant and direct impact on improved system quality.

- **Impact of attitudes toward technology on business intelligence success (H10a,b)**

Within hypothesis H10a, the proposal was forwarded of a positive impact from attitudes toward technology on system quality, and in the study context there is positive support for this hypothesis. Hypothesis H10b, however, proposed a positive impact on information quality from the attitudes toward technology, with this study's findings offering no support for the hypothesis. The research findings do not offer support to Wang et al. (2006), who discovered an insignificant impact on IS system quality from attitudes toward technology. The process for the delivery of IS success is through the adoption of training and development in order to change the attitudes of users occupying the human aspect of the system (Burton-Jones et al., 2017). Since there can be particularly negative attitudes with regard to new IS projects, radical projects for change including enterprise resource planning systems can fall into a 'death spiral' and consequent failure (Badewi et al., 2013). To summarise, it can be said from the main findings that Jordanian mining companies confirmed an impact on BI success from attitudes toward technology. The findings in regard to hypothesis 10a confirm the significant impact from attitudes toward technology on BIS quality within the direction predicted. Based on the results, it is apparent that the greater the feeling amongst employees that they are able to use the technology, then the greater the attitudes towards the BIS will be enhanced, thus leading to the success of the system as the influence on increasing the success of the BIS is both significant and direct.

- **Impact of trust on business intelligence success (H11a,b)**

Within this research, hypotheses were made of a direct and positive impact from trust on system quality (H11a) and information quality (H11b). In the context of BIS, the findings demonstrated the existence of an insignificant relationship between information quality and trust, and between system quality and trust. The findings differ from previous investigations that examined the direct influence on IS success from trust, finding the significance of trust within successful IS project implementation in a variety of contexts (Zhang and Prybutok, 2005; Lee et al., 2007). Trust in IS has importance for delivering the successful implementation of systems (Nicolaou and McKnight, 2006; Hasan and Abuelrub, 2008), while it has been shown that enhanced levels of trust promote information quality and improved systems (Zhang and Prybutok, 2005; Lee et al., 2007; Cyr et al., 2009). The cited studies demonstrate a strong and positive relationship between BIS success and trust in the BIS, while this study's findings revealed an insignificant relationship in the direction predicted between BI success and system trust. Those hypotheses were thus not supported from the results of the survey of the mining sector in Jordan. Furthermore, despite a careful re-examination of the literature, it is not immediately apparent what the reasons are for this unexpected finding, and so further research is required so that potential explanations can be explored.

- **Impact of user participation on business intelligence success (H12a,b)**

Within this research, the hypotheses were made of a positive and direct impact from user participation on system quality (H12a) and information quality (H12b). The data revealed an insignificant relationship between system quality and user participation, while user participation was found to have a significant impact on information quality. The study findings, therefore, align with the results shown in previous research that suggest a strong relationship existing between increased BI success and user participation (Yeoh and Koronios, 2010; Dawson and Van Belle, 2013; Grublješič and Jaklič, 2015; Yeoh and Popovič, 2016). Those findings also agree with the work of Mesaros et al. (2016), which notes that user participation may have an impact on BIS success. Contrasting with the work of Mesaros et al. (2016), Xu and Hwang (2007) found that user participation had an effect on system quality but not on information quality. User participation occurs when project tasks and roles are assigned to users, which results in enhanced communication of their needs and also helps in ensuring there is successful implementation of the system (Hartwick and Barki, 1994). To summarise the main findings, it may be expressed that the participants from Jordanian mining companies noted that user participation has a significant impact on the provided information quality. The findings in regard to hypothesis H12b offer confirmation that the impact of user participation on increasing BIS data and information quality is significant. Based on these findings, it can be asserted that enhanced and increased participation for users during the implementation of BI may play a significant role in BI success, as it has a significant and direct impact on increasing information quality.

- **Impact of system quality on information quality (H13)**

Within this research, the hypothesis was formed of a direct and positive impact from system quality on information quality (H13). A significant relationship was shown between system quality and information quality, and since this is in agreement with previous studies it can be asserted that system quality impacts directly on BIS information quality. The finding confirms those obtained from previous investigations that found system quality to directly influence in that regard (Wixom and Watson, 2001; Xu and Hwang, 2007; Hwang and Xu, 2008). The relationship strength between information quality and system quality discovered within this study reflects the extent that mining companies in Jordan using the BIS may have an up-to-date system that offers accurate information, and thus have information outputs of value to BI use. In light of this, a highly sophisticated BIS results in an information format with high output and a high degree of information content. The finding related to hypothesis H13 provide confirmation that the impact of system quality is significant on increasing the quality of the BIS information. Based on this finding, it may be expressed that BIS enhancement through the utilisation of modern and user-friendly technologies may present users with information in a more easily understood format, thereby enabling them to effectively utilise the BISs. Furthermore, high quality system flexibility results in higher information content quality.

- **Impact of business intelligence system success on decision quality (H14, H15)**

Within hypothesis H14, a positive impact of BIS success on decision quality was forwarded. The results revealed an insignificant relationship between decision quality and system quality. However, hypothesis H15 proposed a positive impact on decision quality from information quality, which was supported in this study's context, in agreement with previous studies and meaning that the information quality offered from the system of BI directly impacts on decision quality. The finding confirms those obtained within other research that showed information quality has a direct impact on decision-making quality (Bantel and Jackson, 1989; Amason, 1996; Wixom and Watson, 2001; Xu and Hwang, 2007; Hwang and Xu, 2008). Furthermore, previous research into decision support systems argues that decision quality could improve with enhanced information quality depending on the quality of the decision-maker (Raghunathan, 1999), while Visinescu et al. (2017) found a positive influence on decision quality from information quality. The argument has also been made that characteristics that are attributable to the team of decision-makers influence decision quality (Murray and Crothers, 1989; Amason, 1996). To summarise the main finding, it may be stated that the relationship strength between decision quality and BI success revealed by this research reflects strongly that mining companies within Jordan that more deeply use BI in the provided data of the BIS tend to make better quality decisions. Furthermore, the findings suggest that the system of BI may help in the improvement of decision quality in circumstances where there is a sufficient or greater volume of information and data. The findings in respect to hypothesis H15 confirm the significant influence that BI success has on increasing BIS quality. Based on the results, it may be expressed that the promotion and maintenance of the BIS may play a significant role in the performance of the company, as it significantly and directly impacts on increasing decision quality.

6.4 The mediating impact of system quality and information quality

To address the fourth objective of the research, namely, Analysing the mediating impact of the system and the information quality of BI implementation success, this study offers insights into the influence of successful BI implementation on decision-making quality that could be transferred through the utilisation of the information offered from the system of BI within the Jordanian mining sector. The analysis provides empirical evidence to support decision-makers in identifying the current usage of the BIS to facilitate efforts to enhance the performance of the company. Moreover, the analysis highlights potential lags in BIS implementation that companies could explore so that the comprehensive benefits of adoption can be realised. Such knowledge has importance within the mining sector in terms of helping to secure superior capacity for the delivery of high-quality decisions, and consequently enhanced performance. The IS success model of DeLone and McLean (1992) was employed in the conceptualisation of the measurement of BIS success, which consists of six categories: i) system quality, ii) information quality, iii) user satisfaction, iv) use, v) organisational impact, and vi) individual impact.

Within studies of BI, the variables chosen for measuring BI success tend be user satisfaction, system quality and information quality (Wixom and Watson, 2001; Xu and Hwang, 2007; Hwang and Xu, 2008). This study, therefore, adopted these variables for the measurement of the impact of the implementation factors on the three variables of IS success: i) information quality measures IS output, ii) system quality measures system performance, and iii) decision quality/user satisfaction measures the response of users to the use of the IS output. Previous research on IS forwarded system quality as a significant enabler of information quality (Seddon, 1997; Setia 2013). Recently, it has also been noted that information quality is affected by system quality, which in turn has an effect on user satisfaction (McGill et al., 2003). In the BI success context, the literature has shown that the relationship between information quality and implementation factors is mediated by system quality (Wixom and Watson, 2001; Xu and Hwang, 2007; Hwang and Xu, 2008). Furthermore, Visinescu et al. (2017) found that the relationship between user satisfaction/decision quality and system quality is mediated by information quality. This study provides an examination of the impact of the mediation of system quality on the relationship between BIS information quality and implementation factors, and the impact of the mediation of information quality on the relationship between decision quality and system quality within the context of the mining sector in Jordan. The findings revealed that the indirect effects of the constructs of management support, business plan and vision, IT infrastructure, attitudes toward technology and champions on the construct of information quality were significant. The findings also forwarded evidence of an indirect dominating effect from system quality on the construct of decision quality. The findings suggest just one partial mediation effect that is negative, namely the construct of resources on information quality, and that the model had no full mediation. The study findings are consistent with previous research presented by Wixom and Watson (2001), Xu and Hwang (2007) and Hwang and Xu (2008). Moreover, the findings highlight the role played by system quality in the relationship between BIS information quality and the implementation factors, as well as the role played by information quality in the relationship that exists between decision quality and system quality in the mining sector in Jordan. Based on the results, it may be expressed that enhanced management support, business plan and vision, attitudes toward technology and IT infrastructure will lead to improved BIS quality, which in turn will result in higher quality information content that will have a positive impact upon decision quality.

6.5 **Validation and revision of the framework for the research**

In order to address the fifth research objective, that is, developing and validating a conceptual framework that defines the impact of successful BI implementation on the quality of decision-making in the context of the Jordanian mining sector, this research utilised a number of procedures for the development and validation of the conceptual framework for the research. Initially, following a review of the literature related to the model for IS success and BI implementation, there was identification of the primary factors for use in analysis of the quantitative data, and then the construction of the proposed study model. A total of twelve implementation factors were adopted for measurement of the effect on the success of the BIS—business plan and vision, management support, champions, resources, change management, data source systems, project management, IT infrastructure, team skills, trust, attitudes toward technology, and user participation— which were analysed through three variables adopted from the model for IS success: user satisfaction, information quality and system quality. Then, CFA was applied in order for the validity of the proposed measurement model to be examined, while CFA was also employed at the next stage so that the model could be accepted or rejected. The measurement model that resulted showed a satisfactory fit, following a number of modifications. As noted in Chapter 5 (section 5.4), an acceptable fit level was shown by the structure model to the data (AGFI = 0.829, GFI = 0.849, TLI = 0.969, IFI = 0.972, RMSEA = 0.026 and CFI = 0.972). The results of the CFA therefore confirmed that the responses of the research participants supported the theoretical as well as the conceptual uniqueness of all the proposed factors for this study. Once the best-fitting measurement model was determined, the convergent validity for this research was analysed through the factor loading, AVE and CR. The construct of this research exceeded the smallest prerequisite for factor loadings, AVE and CR, respectively, with all the values suggesting that the items used within the measured framework had considerable convergent validity. Discriminant validity was analysed by this research through the contrast of the square of the correlation between two variables of the research against the AVE weights for any two items. Discriminant validity is essential when the squared correlation amongst the constructs is lower than the AVE. Those outcomes of research showed a discriminant validity level that is significant because, for all constructs of the research, the squared correlation was lower than the AVE values. Furthermore, the value of Cronbach's alpha indicated that the questionnaire had a high degree of reliability. All of the results, therefore, showed evidence of convergent and discriminant validities that were strong for the questionnaire used in the research and the measurement model factors. Once the confirmatory techniques had been completed through the CFA, analysis of the structural model was undertaken for the proposed model through the use of SEM. Building on the relationship forwarded in the work of DeLone and McLean (1992), in addition to the revised measurement model, there was initiation of the proposed model (the structural model). Therefore, the measurement model was utilised as a foundation for the building of the structural model of the research through the addition of estimated relationship paths between the factors for IS success and the implementation factors. The final model of research, as shown in Figure 5.10 (Section 5.4.2), is supported by the study findings, which also support the causal relationships between the variables of the model. As is apparent from the statistics of SEM fit within Table 5.13 (Section 5.4.2), an acceptable fit indices set was yielded by the final model, revealing a confirmed fit of the model with the relevant empirical data. In accordance with the final version of the research model, the implementation factors for the successful system of BI were determined through the use of six factors that impact the system quality/technical success (i.e. management support, business plan and vision, resources, attitudes toward technology, champions and IT infrastructure). In addition, three factors (i.e. user participation, project management and data source systems) were found to have an effect on information quality/semantic success. Furthermore, the final version of the model determined the impact of BI success that results in decision-making of high quality through information quality offered by the system of BI. Elucidation of the structural model's predictive power was carried out through explaining the variance (R^2) of the endogenous constructs, with the results providing confirmation that the structural model explained a large proportion of the variance within those endogenous factors. The results of the structural model give the suggestion that the indicators used in the research explain only 28.1% of the variability of decision quality, just 33.2% of the variability of information quality, and 55.2% of the system quality variability in the provision of satisfactory power of explanation. Meanwhile, there was a value of 38.8% for R^2 (average variance explained by the model). In following Hung et al. (2016), the predictive power of models is established within successful traditional studies of BI implementation that have a focus on predicting implementation factors with respect to BI success; however, it was discovered that 60% of the user satisfaction variance was explained by their model of BI success and 48.9% in the system effectiveness overall. Then, Işık et al. (2013), who employed the model for BI success within the United States, discovered that their model explained around 55.7% of the variance within BI success. The model developed in the work of Hwang and Xu (2008) was found to explain approximately 27% of the variance of system quality, 40% of the variance of information quality, 41% of the variance of organisational benefits, and 34% of the variance of individual benefits. Puklavec et al.'s (2017) extended model of BI success explained 52.9% of the total variance of adoption of BI, while a success model for BI implementation developed by Woodside (2011) explained 73.8% of the factors of success within the United States. Compared to other studies of BI implementation success, this research provides results that confirm the developed model as having average explanatory power, and that it has durability in the successful implementation of BI within Jordan. Overall, the conclusion may be drawn from the discussion above that the proposed model within this research offers a sound understanding of the implementation factors that have an effect on the success of BI within Jordan. Furthermore, this result also suggests that the model may serve to adequately conceptualise IS success generally, and BI success in particular.

6.6 Chapter summary

This chapter reflected on the outcomes derived from the hypotheses of the research, as presented in Chapter 5, through the use of a structural equation model. First, there was discussion of the key factors for BI implementation within the Jordanian mining sector, followed by consideration of the outcomes that had an emphasis on those significant implementation factors impacting on the success of BI. Nine of the twelve implementation factors tested within the preliminary model of research were found, overall, to have a positive and significant influence on the success of the system of BI. The following implementation factors were therefore integrated into the final version of the model: business plan and vision, management support, champions, resources, IT infrastructure, attitude towards technology, project management, data source systems and user participation. Three implementation factors were found to have no significant impact on BI success, and as such were excluded (i.e. change management, trust and team skills). There was also presentation of a discussion related to the indirect and direct impact, so that the mediation impacts of information quality and system quality could be shown. The findings revealed that the indirect effects that the constructs for business plan and vision, management support, champions, IT infrastructure and attitudes toward technology had on information quality were significant, with an indirect effect from system quality on the construct for decision quality. The final proposed model for BI implementation success for this study underwent validation, and there was confirmation and proof of its effectiveness in providing explanation of successful BIS implementation. Chapter 7 which follows provides the overall conclusions from the study, along with a discussion of its theoretical contributions, and the implications in practical terms. The focus is also placed on the study limitations, which represent potential research avenues for future work.

Chapter Seven:

Conclusion

7.1 Introduction

Within this chapter there is an assessment of the primary study conclusions in relation to the aim and objectives of the research. This chapter also presents the research contributions and limitations, along with recommendations for potential research in future. Following this brief introduction, section 7.2 presents a summary/study overview, while section 7.3 sheds light on how the research objectives were achieved. Following on, section 7.4 provides a discussion of the research contributions in relation to the theoretical, practical and economic contributions. The study limitations are given consideration within section 7.5 and, finally, recommendations for potential future research are discussed within section 7.6.

7.2 Study summary

The study commenced with an introduction to the background of the research, as well as the associated motivations and problems, so that consideration could be given to the significance of the research and the potential it has to contribute to the fields of IS and BI. The discussion revealed that many opportunities and benefits have arisen for the Jordanian mining sector from the growth of BI, and that the sector is considered one of the most significant contributors to the national economy; however, it was shown that the Jordanian mining sector faces considerable challenges with regard to IS and the management of the huge volume of information that supports the making of decisions. For continued survival in the face of significant regional competition, the mining sector requires BI implementation as a system for supporting decision-making, since this helps to support the management, development and distribution channels of communication of intangible resources for the enhancement of the decision-making process, while offering a broad range of opportunities for improving manager capability with regard to the making of better business decisions through the use of accurate data, reaching the right customers in a timely manner, improving marketing and sales, and consequently increasing revenue. There has, however, been a considerable lack of empirical research exploring the implementation of BI within countries in the MENA region, with a paucity of such studies undertaken in Jordan, and even less so that have a particular focus on the mining sector in Jordan.

The literature review revealed that the existing models for explaining the implementation factors affecting the success of BI within mining companies are, at best, limited. This study, therefore, aimed to develop a comprehensive framework for presenting an improved rationale for success in BI implementation. As well as the general lack of research within the Jordanian mining sector, there is also a lack of research that investigates whether implementation factors have an impact on different variables of BI success. This study therefore included an examination of those implementation factors that have a bearing on BI success, and thus contributes towards understanding the extent that success in system implementation has on success factors for the system, leading to enhancements in decision quality, particularly for the field of studies related to BI.

Based on the literature review, there was the development of a conceptual framework for the examination and identification of implementation factors within the Jordanian mining sector and whether they have an impact on BI success. This conceptual framework was constructed from a combination of different models including the IS success model proposed by DeLone and McLean (1992), the data warehouse success model proposed by Wixom and Watson (2001), the data warehouse success model proposed by Hwang and Xu (2008), and the model for implanting BIS developed by Yeoh and Koronios (2010). The selection of the implementation factors chosen for use in this research was founded upon those factors that were most dominant and/or frequently cited within previous studies. As such, twelve factors were chosen for the examination of their impact on BI success. The quantitative method was applied to the study through the adoption of a positivist philosophy and a deductive approach, within which a web-based questionnaire survey was utilised to obtain quantitative data for the testing and validation of the proposed framework. The study data were acquired from managers working within the Jordanian mining sector. In total, 372 responses from the sample were deemed usable. The technique of SEM was employed in testing the relationships hypothesised through the use of AMOS (v.25), while the demographic statistics were analysed using SPSS (v.25). The primary conclusions reached for this research are summarised in section 7.3 below, with explanation of how the aim and objectives of the study were achieved.

7.3 Achievement of the study aim and objectives

The aim of this research is to advance knowledge and understanding of the implementation of BI, the factors that influence that implementation's success, and how BI impacts on the quality of decision-making in the Jordanian mining sector. The achievement of this research aim has been through systematically addressing the objectives of the research, as highlighted within the subsections presented below.

- **Objective 1: Identifying the implementation factors that affect business intelligence success**

The first objective of identifying the implementation factors that affect BI success was achieved through a critical review of literature related to implementation factors for BI, as well as theories and models of success. The literature review was undertaken so that an in-depth understanding could be gained of the procedures and processes involved in BIS implementation (see Chapter 2 and Chapter 3). The review focused on the identification and the prioritisation of key implementation factors deemed impactful to BI success. Based on that critical review, through scrutiny of the models of implementation and IS/BI success, there was identification of twelve implementation factors that were employed in the development of the general conceptual framework for the study and associated hypotheses. From the framework and hypotheses, the measurement model and the structural equation model were created. The implementation factors that were identified as a result of that process, which were considered to impact on the success of BI, were business plan and vision, management support, champions, resources, project management, team skills, change management, data source systems, IT infrastructure, attitudes toward technology, trust, and user participation. Identification of those factors was essential in developing a theoretical model that facilitated in acquiring an understanding of the relationships amongst them and their effect on BI success.

- **Objective 2: Assessing the business intelligence implementation factors in the Jordanian mining sector**

There was achievement of the second objective of assessing the business intelligence implementation factors in the Jordanian mining sector through the exploration of the descriptive statistics for this research in Chapter 5 (Section 5.3.2), and as discussed further within Chapter 6 (Section 6.2). A lack of understanding along with a failure to address implementation factors are considered the primary causes of BIS failure. Meanwhile, an inherent characteristic of BI success is that considerable time is required for measurement and the bringing forward of results. If implementation factors for BI are not identified prior to implementation, then significant resources may be wasted during the process of implementation. This research discovered that most of those factors proposed were prevalent within the process of implementation of the BI projects within the Jordanian mining sector. There is importance for those working within that sector to have an understanding of the presence of those particular factors, both prior to and during the implementation of BI, so that appropriate steps may be taken to address issues. This research found that the implementation factors of BI and their related constructs for management support, business plan and vision, resources, champions, team skills, project management, attitudes toward technology, IT infrastructure, data source systems, user participation and trust all had relatively high scores within the Jordanian mining sector. The factor of change management, meanwhile, had a score that was much lower. Interestingly, of the three implementation factors that scored highly, were those factors that had a greater association with social and user aspects (i.e. team skills and attitudes toward technology). Of those implementation factors that, arguably, have more concern with the practices and readiness of organisations, business plan and vision, and resources had scores that were slightly lower, while change management had the lowest score. Therefore, the study results also demonstrate the significance of the social and user aspects in the success of BI, and thus it can be reasonably concluded that those aspects highlight the need for a drive to encourage the further training and education of employees and managers within the BIS.

- **Objective 3: Testing the impact of the implementation factors on business intelligence success**

There was achievement of the third objective of testing the impact of the implementation factors on business intelligence success through the SEM part of the research, as shown in Chapter 5 (Section 5.4) and discussed further in Chapter 6 (Section 6.5). Within Chapter 3, a conceptual framework was put forward related to success in BI implementation within the Jordanian mining sector, with the intention of identifying and prioritising the implementation factors that are influential for success in BI, and the impact of BI success on decision quality. SEM had the primary objective within this study of examining the underlying hypotheses so that implementation factors impacting on BI success within the Jordanian mining sector could be identified. Hypotheses testing helped in meeting this particular research objective. There was the adoption of 27 causal paths that represented the research hypotheses, to the fitting measurement model. The hypotheses had the aim of determining causal relationships between the implementation factors and success of BI within the structural model. The results from AMOS (v.25) showed that eleven of the 27 paths had significance (see Figure 5.10). The final results suggested that six factors impacted on system quality (technical success): management support, business plan and vision, resources, champions, attitudes toward technology and IT infrastructure. Furthermore, the results showed that three factors impacted on information quality (semantic success): data source systems, user participation and project management. Moreover, this study has confirmed that there are major effects from system quality upon information quality, and that information quality impacts significantly on decision quality.

- **Objective 4: Analysing the mediating impact of the system and the information quality of business intelligence implementation success**

The research objective of analysing the mediating impact of the system and the information quality of BI implementation success was achieved in the SEM section of the study, as shown in Chapter 5 (Section 5.4) and discussed further in Chapter 6 (Section 6.5). System quality was used within this study as a mediator between information quality and the implementation factors, while information quality was used as a mediator between decision quality and system quality, both within the context of the mining sector in Jordan. Based on the analyses of indirect and direct effects offered by AMOS (v.25), it could be seen that the constructs of management support, business plan and vision, attitudes toward technology, champions and IT infrastructure had an indirect and significant effect on information quality. Moreover, in a corresponding way, it was found that system quality also had an indirect and significant effect on decision quality via information quality. The variable of system quality, therefore, may be considered as a central contributor of information quality, whilst information quality itself can also be considered as a central contributor of decision quality. The implication from these results is that both of the constructs can be considered as essential within the model of the research.

- **Objective 5: Developing and validating a conceptual framework that defines the impact of successful business intelligence implementation on the quality of decision-making in the context of the Jordanian mining sector**

Within Chapter 3 (Section 3.4), a conceptual framework was developed and proposed in order to provide a rationale and context for the development of hypotheses and for the systematic detection of distinct causal relationships between the latent variables identified. As explained earlier, a conceptual framework was developed within the study for the illustration of the impact from twelve implementation factors on BI success (information and system quality): business plan and vision, management support, champions, resources, project management, team skills, change management, data source systems, IT infrastructure, attitudes toward technology, trust, and user participation, and then the contribution towards decision quality. Furthermore, the framework explored the role in mediation of information and system quality within the relationships between the implementation factors, information quality and the decision quality. Following the determination of the best fit for the measurement model within Chapter 4, there was the application of CFA in order to examine the validity for the hypothesised measurement model. CFA was employed as the next step so that the proposed model could be either accepted or rejected. After a number of modifications, the measurement model that resulted showed a model fit that was satisfactory. Once the confirmatory techniques had been completed through the use of CFA, structural model analysis was conducted on the proposed model through the use of SEM. The measurement model was utilised as a foundation on which the structural model of the research was built, through the addition of the estimated relationship paths between the implementation factors and success of BI.

The research has shown that there were satisfactory results for the research model in providing explanations for the impact of numerous implementation factors on BI success within the mining sector in Jordan, as explained in Chapter 3. Additionally, there was support for the numerous relationships amongst the constructs that the structural model had assumed. Furthermore, there was explanation of the predictive power of the structural model by way of the variance explained (R^2) for the endogenous constructs. The results provided confirmation of a considerable proportion of variance within the endogenous factors, as explained by the structural model. The results of the structural model suggested that only 28.1% of the variability in decision quality was explained by our indictors, 33.2% of the variability in information quality and 55.2% of the variability in system quality, and thus satisfactory explanatory power was provided. R^2 (average variance explained) by that model was 38.8%. Therefore, this study plays a pivotal role in the provision of further evidence to support the suitability of application of the conceptual framework for examination of the impact that the implementation factors have on BIS success within the Jordanian mining sector. Figure 7.1 serves to illustrate the structure of the final model for the research and the relationships between the nine final implementation factors on the variables for BI success (semantic, technical and effectiveness level).

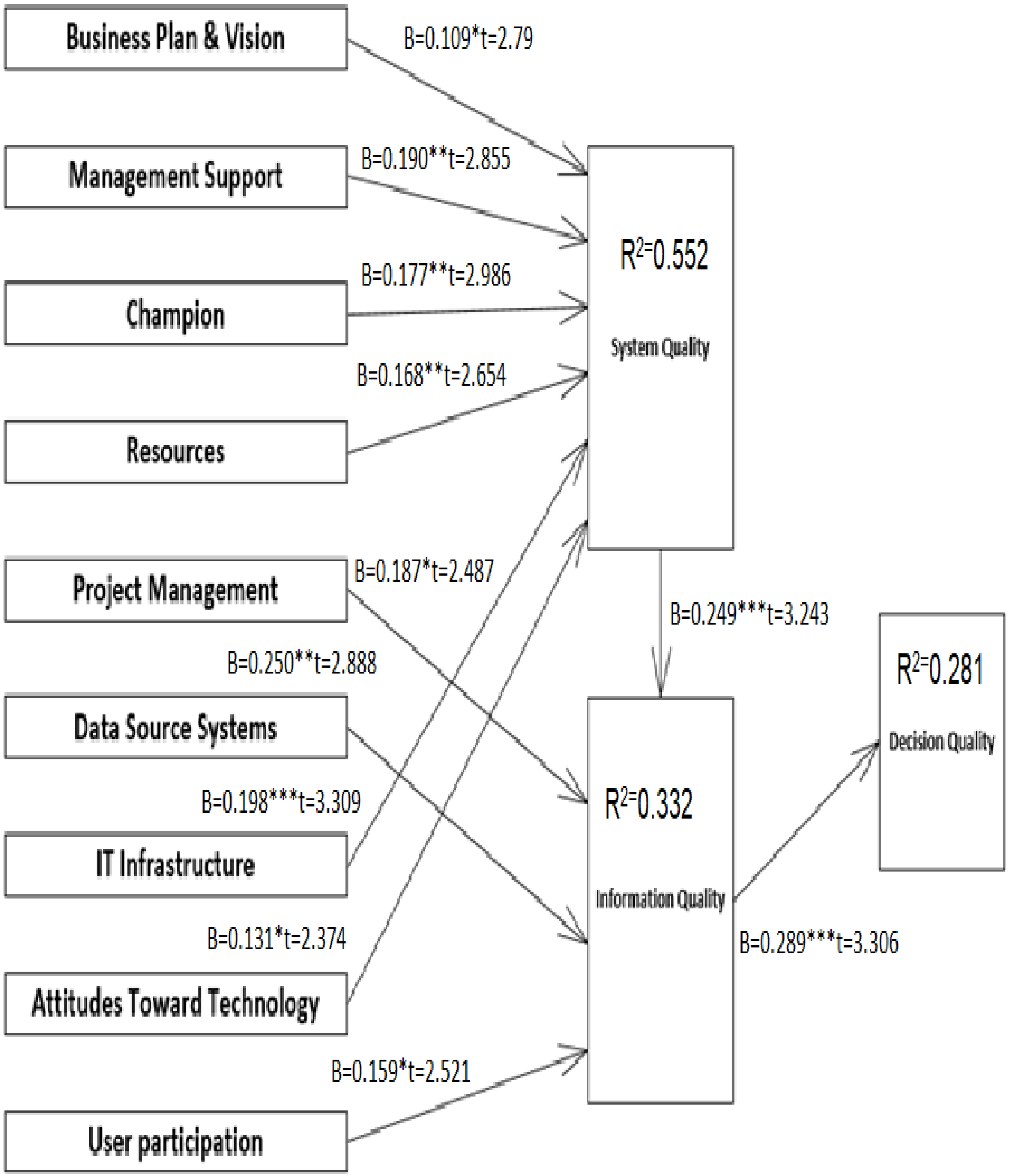

Figure 7.1 Final research model
(Source: the author)

To summaries, Table 7.1 shows each objective and how the research objectives were achieved.

Table 7-1: Meeting the research objectives

Objectives	Objective achieved
Objective 1: Identifying the implementation factors that affect business intelligence success	literature review (Chapter 2 and 3)
Objective 2: Assessing the business intelligence implementation factors in the Jordanian mining sector	Exploration of the descriptive statistics (Chapter 5 and 6)
Objective 3: Testing the impact of the implementation factors on business intelligence success	Testing hypotheses through SEM technique (Chapter 5 and 6)
Objective 4: Analysing the mediating impact of the system and the information quality of business intelligence implementation success	Analyses of indirect and direct effects (Chapter 5 and 6)
Objective 5: Developing and validating a conceptual framework that defines the impact of successful business intelligence implementation on the quality of decision-making in the context of the Jordanian mining sector	Validating the model through the results of CFA, structural model, and R2 (Chapter 5 and 6)

In general terms, the research aim could not have been reached successfully without the realisation of the aforementioned study objectives.

7.4 The research contributions

The contributions made by this research project are presented below within three sections, that is, the theoretical contributions, practical contributions and economic contributions.

7.4.1 Theoretical contributions

In relation to the theoretical contributions, there are six different aspects worthy of consideration as follows:

Firstly, this study identified a research problem within the implementation of BI. Existing knowledge related to BI implementation is enriched by this study through its identification of nine implementation factors that have an effect on BI implementation success. A lack of studies related to BI implementation within the literature is highlighted, and in particularly the lack of social and user aspects for the implementation factors is highlighted in Chapter 2 in the review of the literature and in Chapter 3 related to the research framework. The results indicate that the considered implementation factors may impact positively upon BI success. Of the twelve implementation factors considered, six of them were shown to be capable of impacting on the system quality (technical success) of the system of BI within the context of the mining sector in Jordan, that is, management support, business plan and vision, resources, champions, attitudes toward technology and IT infrastructure. Furthermore, within that context, three implementation factors were found to have an impact on information quality (semantic success): data source systems, user participation and project management. The results substantiate the importance of explicit consideration of those factors within the research of BI implementation. Furthermore, the study shines light on how social and user aspects have an impact on success in the implementation of BI projects. The framework developed was able to depict how BI success is driven, in part, by complementarities that exist between the implementation factors and the key social and user aspects of attitudes toward technology. As such, this study adds to the associated literature which, for several years, has had a primary focus on the organisational, project, process and technical aspects. This research thus contributes to a fresh dimension in understanding the factors that have an impact on BI implementation success.

Secondly, this study's contribution to understanding of the success of IS in general, and more specifically, success in BI, stems from the new model's development. Within the study, a framework was built that involved the amalgamation of two different theoretical perspectives, namely the theory of implementation factors and the IS success model proposed by DeLone and McLean (1992). Through combining these models, a significant contribution to theory was attained. The selected implementation factors helped in filtering down those necessary factors that must be present within BI project implementation. Equally, the IS success model was employed in the assessment of the BI implementation in the subsequent assessment of the BI implementation. Through assessment of BI implementation, it is possible to ascertain whether the appropriate determinants are in place. Much research has only adopted one of those approaches, but not both. Therefore, this study demonstrates that both theories can be used together in a complementary manner. In addition, it was pointed out from the literature that much of the research in this field has been theoretical. In this study the theoretical aspects have been overcome through the use of IS theories within the framework development, while the empirical research results provide evidence that not all of the implementation factors used had statistical significance. Critics might claim that experimentation with various implementations is an ineffective use of time; however, the research motivation has been to investigate the components required for an implementation to be successful.

Thirdly, this study has also contributed to the achievement of an understanding of those complex relationships, both indirect and direct, that occur between implementation factors that have an association to success in BISs. Moreover, the degree of influence of all those factors on the others has been investigated, so that the likelihood of success of those systems can be increased, and the possibility of failure in the implementation and subsequent operation reduced. As demonstrated within Chapter 2 and Chapter 3, the majority of studies have placed their focus on gaining an understanding of the CSFs or the implementation factors that make BIS success more effective within companies. Those studies, however, have not paid attention to the indirect effects between the implementation factors and the information quality through the system quality in terms of the success of the BIS. This study provides further information with regard to indirect influences (i.e. the business plan and vision, management support, champions, IT infrastructure and attitudes toward technology) on semantic level success (information quality), and the indirect influence of the technical level (system quality) on decision quality.

Fourthly, the overall study findings may guide future work within various areas of IS. DeLone and McLean's (1992) model of IS success has been validated by this study through demonstration of how the variables of system success (information and system quality) affect decision quality both indirectly and directly through their influence on user satisfaction with the information provided from BIS. This is a significant validation of their model and ought to reflect transferability to other research projects that have the aim of identifying which BI implementation factors may impact on system success and how they do so. The model may be transferable to various other IS contexts such as other sectors of the economy including hospitality, banking, healthcare and the various ministries of government.

Fifthly, the design of this study has been intended to bridge the gap that was seen to exist between knowledge related to BI implementation, and success within the MENA region in general, and within Jordan in particular. The research originality comes from it being the first such study undertaken within the Jordanian mining sector. These facts serve to provide justification for conducting the study and other kinds of prospective study within that context, or within other contexts that have similar circumstances.

Finally, BIS types were identified within the study and the existing implementation factors within the mining sector in Jordan were explored. This is the first study to undertake such an approach, and so it provides an empirical platform upon which future researchers can investigate BI implementation further within the context of Jordan. There is an expectation that the research will provide much-needed impetus to other research in relation to success in BI implementation within the Jordanian context.

7.4.2 Practical contributions

In terms of the practical contributions, there are considered to be six noteworthy aspects, as follows.

Firstly, given the beneficial offerings from BI, the study findings provide insights related to what kind of environment is conducive for effective and successful forms of BI within decision-making. Considering the perspective of Jordan, this study has sought to shed light on the impact that implementation factors have on BI within the mining sector. It is hoped that the empirical evidence can change motivation with respect to the implementation of BI from mere compliance to a sense of awareness of its business worth. Other sectors and organisation types may learn from this research and then emulate the positive experiences within other companies that have implemented a BI project successfully.

Secondly, this research has provided practitioners with a process map illustrating the implementation of BI that can help in the identification of relevant BI implementation factors for their particular organisations, while determining the impact of the implementation factors on each of the levels of success in BI (i.e. technical, semantic, and effectiveness). Moreover, there has been determination of the most appropriate strategy and method for BI implementation, with the acknowledgement of the management of the capability requirements and the required BIS for achievement of the goals with the best intention for BI implementation that would lead to enhanced decision-making quality.

Thirdly, there is a need for decision-makers and BI practitioners to ensure there is sound development in the key implementation factors in order to serve as drivers facilitating successful BI implementation. There is also a need for such decision-makers and BI practitioners to eliminate or at least decrease the impact and intensity of implementation factors. In terms of relevance for practice, the findings from this research could help practitioners in the adoption of more holistic approaches to BI implementation, as well as in the recognition of the need to identify and manage the implementation factors within each of the key stages of the process of implementation.

Fourthly, this research has also put forward useful guidelines capable of enhancing BI implementation success and the decision quality that results from the implementation of BI, namely, business plan and vision, management support, champions, resources, project management, data source systems, IT infrastructure, attitudes toward technology, and user participation. An assessment approach is thus provided for current practice effectiveness in relation to BI implementation success and the processes of its evaluation.

Fifthly, in terms of practicality, the new framework has a specific design for a country with a developing economy, and thus the particular organisational types therein mean that the research offers a contribution to knowledge in an in an under-researched subject area. Thus, the results that contributed to the framework development in relation to BI implementation within the Jordanian mining sector could also have applicability within comparative studies for other developing countries and other countries within the MENA region in particular.

Finally, due to the sample nature, the methods employed in the selection of participants and the demographics of the mining sector, the study findings could be generalised to the population of the study (i.e. the mining sector in Jordan), as well as potentially other similar mining contexts in the MENA region, along with similar countries in other regions.

7.4.3 Economic contribution

There is considered to be one key economic contribution of the study. The sector of mining is one of the main contributory sectors for the Jordanian economy, particularly in respect to GDP, and there is a desire for it to remain profitable and competitive. There is a perception that BISs are fundamental keystones that offer the associated benefit of helping yield a sound return on the investment made. Therefore, there is justification for robust investment within the sector, directed towards the implementation of BI. However, as discussed within Chapter 2 in relation to the motivation for the study, the market for BI struggles with high rates of failure, which can have an impact that ripples negative effects through the economy. This would be the case if those benefits associated with the implementation of BI for the sector are not realised for the return on investment and the business strategies. Drawing on the aforementioned implications for practice, this study makes a significant contribution through the provision of a novel framework for managers working in the mining sector, which can be utilised within their strategies for implementation. Since there are numerous organisations that have failed in their implementation of BI, this study may be utilised as an index for the measurement of failure points through the developed model in order to promote understanding and address the key points of focus identified. Therefore, an economic contribution is made by this research.

7.5 Study limitations

The limitations of the study have been grouped below into five aspects.

Firstly, the process of BI implementation involves the top decision-makers within an organisation, although this typically depends on the chief executive. So that the hypotheses could be verified, the data within this research were collected from people occupying all management levels within the organisational hierarchy. This may have resulted in a situation whereby opinions from middle and operational managers, and top management executives were given equal weight whilst, in reality, there may be considerable differences in how they make decisions. The method of sampling that was adopted within this study, for the classification of decision-makers with equal weight, could have led to an assessment that was inaccurate in respect to the relationships between BI success and the implementation factors used. That limitation could be overcome through the investigation of implementation factors via the collection of data from specific segments of the population, such as only the top management, which would enable a more focused appreciation with regard to the process of implementation within the mining sector, and therefore enable improved understanding with regard to the relationship between the dependent and independent variables.

Secondly, in respect to the research findings' generalisability, this study may have suffered from an assumption that there are inherent similarities in mining sector companies and so the collected data, gathered by means of a simple process of random sampling, may have been erroneously assumed as having homogeneity. There can, in reality, be unique factors for each of those companies, and it may be flawed to assume that the research findings have consistent applicability to all of the companies, despite the frequency of common characteristics within the mining sector. Therefore, the research findings' generalisability for this study could be questioned. An investigation that has more focus on the type of company may lead to results with greater consistency that could then be accepted as having greater generalisability.

Thirdly, the use of only a quantitative approach assumes the existence of one singular truth (i.e. the assumption that a relationship exists between BI success and implementation factors). Such an assumption leads, inherently, to a researcher ignoring the potential impact of other underlying implementation factors that could pertain to the success of BI. This stance may represent a limitation, preventing the researcher from conducting an investigation of the implementation factor concept. To address this a qualitative approach could have been applied to the research so that certain underlying concepts, not investigated within this study, could be uncovered.

Fourthly, Likert scales were employed in the measurement of the perceptions of participants. The measures were therefore subject to the statements' interpretation by the respondents, although a pilot study was conducted so that the problem could be minimised. Studies in the future need to account for potential issues in interpretation. Moreover, measurements using a Likert scale could result in response bias as participants may wish to avoid the scale extremes and may not always provide honest answers.

Fifthly, the questionnaire survey was the sole instrument employed in the collection of data from the subjects of the study. Thus, a considerable part of the collected data's reliability relied on the respondents having attention to detail when they were providing their responses. Whilst reasonable precautions were made to eliminate threats to data reliability, guaranteeing data reliability was impossible as the questionnaire survey was the sole instrument employed in the collection of data.

7.6 Recommendations for potential research in future

This research has provided substantial evidence with regard to information success in general, and BI implementation in particular. It does, however, raise additional questions that could be addressed by future research. Six recommendations are put forward for consideration, as follows.

Firstly, this study has focused on twelve implementation factors for the purposes of analysis and development of the model. Further research could extend such a study for the inclusion of additional implementation factors. Furthermore, a greater deal of attention and investigation could be focused on the social and user aspects, and their role in the application of BI. The addition of factors would expand our understanding of the process of implementation, and the contributions they make towards the success of BI.

Secondly, there could be extension of the research findings to other kinds of industry, in addition to comparison of the findings with other countries, and comparison of the positions that the respondents occupied and the management levels of the users of BI who make decisions. Such comparisons would provide broader knowledge related to the operationalisation of integrated forms of BI within various contexts, and thereby enhance the model's generalisability.

Thirdly, this study has addressed only three of the six variables identified as variables of IS success within the model of Delone and McLean (1992). Potential future research could give consideration to the impact of the other variables as dimensions of success such as the use, individual impact and the organisational impact in order to acquire more profound insight into how the success of BI is impacted through those particular variables. Moreover, there could be extension of the research outcomes variables such as the effectiveness level and system success of the BI model implementation developed within this study.

Fourthly, there could be further qualitative studies in the mining sector in order to gain deeper knowledge of the process of implementation as a whole, from the initial planning stage prior to implementation, through to the post-implementation phase. Through this, an overview could be gained of the entire process of implementation, which may have benefit for those seeking to implement BI. Moreover, the review of secondary data such as productivity reports may be able to provide further information related to implementation factors.

Fifthly, it is recommended that attitudes toward technology, which serves as a good implementation factor for the successful implementation of BI, ought to be researched further. There is a need for the assessment of its appropriateness, particularly within developing countries where culture is an issue that is critical with respect to the use of technology, and where it may have a significant impact on BI success.

Finally, the testing for external study and model validity was carried out through the re-contacting of the original organisations and respondents, and the confirmation of the findings of the research and model appropriateness. The sample could therefore be developed by other researchers for other organisations and the testing of model validity.

References

Abu-Shanab, E., Abu-Shehab, R. and Khairallah, M. (2015) 'Critical success factors for ERP implementation: The case of Jordan', *The International Arab Journal of e-Technology,* 4(1), 1-7.

Acheampong, O. and Moyaid, S. A. (2016) 'An integrated model for determining business intelligence systems adoption and post-adoption benefits in banking sector', *Journal of Administrafive and Business Studies,* 2(2), 84-100.

Ackoff, R. L. (1967) 'Management misinformation systems', *Management science,* 14(4), B-147-B-156.

Adamala, S. and Cidrin, L. (2011) 'Key success factors in business intelligence', *Journal of Intelligence Studies in Business,* 1, 107-127.

Agarwal, R. and Prasad, J. (1997) 'The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies', *Decision Sciences,* 28(3), 557-582.

Agarwal, R. and Prasad, J. (1998) 'A conceptual and operational definition of personal innovativeness in the domain of information technology', *Information Systems Research,* 9(2), 204-215.

Agarwal, R. and Prasad, J. (1999) 'Are individual differences germane to the acceptance of new information technologies?', *Decision Sciences,* 30(2), 361-391.

Ait-yassine, F. (2012) 'Review of Business Intelligence and Portfolios Performance with Case Study', *European Journal of Business and Management,* 4(9), 66-71.

Al-Jabri, I. M. and Roztocki, N. (2015) 'Adoption of ERP systems: Does information transparency matter?', *Telematics and Informatics,* 32(2), 300-310.

Al-Mashari, M., Al-Mudimigh, A. and Zairi, M. (2003) 'Enterprise resource planning: A taxonomy of critical factors', *European Journal of Operational Research,* 146(2), 352-364.

Al-Mudimigh, A., Zairi, M. and Al-Mashari, M. (2001) 'ERP software implementation: an integrative framework', *European Journal of Information Systems,* 10(4), 216-226.

Al-Shboul, M., Rababah, O., Ghnemat, R. and Al-Saqqa, S. (2014) 'Challenges and factors affecting the implementation of e-government in Jordan', *Journal of Software Engineering and Applications,* 7(13), 1111.

Al-Zubi, Z., Shaban, O. S. and Alnaser, N. (2014) 'The effect of business intelligence tools on raising the efficiency of modern management accounting', *International Review of Management and Business Research,* 3(1), 68.

Al Rawashdeh, R. and Maxwell, P. (2013) 'Jordan, minerals extraction and the resource curse', *Resources Policy,* 38(2), 103-112.

Al Tarawneh, K. (2016) 'A Comprehensive Outlook of Mining Industry in Jordan, Opportunities and Threats', *Open Journal of Geology,* 6(09), 1137.

Aladwani, A. M. (2002) 'Organizational actions, computer attitudes, and end-user satisfaction in public organizations: An empirical study', *Journal of Organizational and End User Computing (JOEUC),* 14(1), 42-49.

Ali, J. M. (2004) 'Information technology in the Middle East',

Allen, D. K., Colligan, D., Finnie, A. and Kern, T. (2000) 'Trust, power and interorganizational information systems: the case of the electronic trading community TransLease', *Information Systems Journal,* 10(1), 21-40.

Alnawafleh, H., Tarawneh, K. and Alrawashdeh, R. (2013) 'Geologic and economic potentials of minerals and industrial rocks in Jordan', *Natural Science,* 5(06), 756.

Alnoukari, M. (2009) 'Using business intelligence solutions for achieving organization's strategy: Arab international university case study', *Internetworking Indonesia Journal,* 1(2), 11-15.

Alshawi, S., Missi, F. and Irani, Z. (2011) 'Organisational, technical and data quality factors in CRM adoption—SMEs perspective', *Industrial Marketing Management,* 40(3), 376-383.

Alter, S. (1999) 'A general, yet useful theory of information systems', *Communications of the association for information systems,* 1(1), 13.

Amason, A. C. (1996) 'Distinguishing the effects of functional and dysfunctional conflict on strategic decision making: Resolving a paradox for top management teams', *Academy of management journal,* 39(1), 123-148.

Amoako-Gyampah, K. and White, K. B. (1993) 'User involvement and user satisfaction: an exploratory contingency model', *Information and Management,* 25(1), 1-10.

Amolo, J., Migiro, S. and Ramraj, A. B. (2018) *The Debatable Paradigm of Mixed Methods,* translated by Academic Conferences and publishing limited, 10-17.

Anjariny, A. H. and Zeki, A. M. (2013) *The important dimensions for assessing organizations' readiness toward business intelligence systems from the perspective of malaysian organization,* translated by IEEE, 544-548.

Anjariny, A. H., Zeki, A. M. and Hussin, H. (2012) *Assessing organizations readiness toward business intelligence systems: a proposed hypothesized model,* translated by IEEE, 213-218.

Arab Potash Company (2018) *Annual Report 2018 English*, Amman: Arab Potash Company

Archimi, C. S., Reynaud, E., Yasin, H. M. and Bhatti, Z. A. (2018) 'How perceived corporate social responsibility affects employee cynicism: The mediating role of organizational trust', *Journal of Business Ethics,* 151(4), 907-921.

Argyrous, G. (2011) *Statistics for research: With a guide to SPSS,* 3rd ed., Los Angeles: Sage Publications.

Arnott, D. (2008) *Success factors for data warehouse and business intelligence systems,* translated by Christchurch: ACIS 2008 Proceedings, 55-65.

Arnott, D. and Pervan, G. (2016) 'A critical analysis of decision support systems research revisited: the rise of design science' in *Enacting Research Methods in Information Systems*, Springer, 43-103.

Aruldoss, M., Travis, M. L. and Venkatesan, V. P. (2014) 'A survey on recent research in business intelligence', *Journal of Enterprise Information Management*.

Arvidsson, V., Holmström, J. and Lyytinen, K. (2014) 'Information systems use as strategy practice: A multi-dimensional view of strategic information system implementation and use', *The Journal of Strategic Information Systems,* 23(1), 45-61.

Audzeyeva, A. and Hudson, R. (2016) 'How to get the most from a business intelligence application during the post implementation phase? Deep structure transformation at a UK retail bank', *European Journal of Information Systems,* 25(1), 29-46.

Aufaure, M.-A., Kuchmann-Beauger, N., Marcel, P., Rizzi, S. and Vanrompay, Y. (2013) *Predicting your next OLAP query based on recent analytical sessions,* translated by Springer, 134-145.

Baars, H. and Kemper, H.-G. (2008) 'Management support with structured and unstructured data—an integrated business intelligence framework', *Information Systems Management,* 25(2), 132-148.

Baccarini, D. (1999) 'The logical framework method for defining project success', *Project management journal,* 30(4), 25-32.

Bach, M. P., Čeljo, A. and Zoroja, J. (2016) 'Technology Acceptance Model for Business Intelligence Systems: Preliminary Research', *Procedia Computer Science,* 100, 995-1001.

Badewi, A., Shehab, E. and Peppard, J. (2013) *Benefit realisation modelling for ERP systems using system dynamics,* translated by 225-235.

Bailey, J. E. and Pearson, S. W. (1983) 'Development of a tool for measuring and analyzing computer user satisfaction', *Management science,* 29(5), 530-545.

Bakunzibake, P., Grönlund, Å. and Klein, G. O. (2016) *E-Government Implementation in Developing Countries: Enterprise Content Management in Rwanda,* translated by IOS Press, 251-259.

Bano, M., Zowghi, D. and da Rimini, F. (2018) 'User Involvement in Software Development: The Good, the Bad, and the Ugly', *IEEE Software,* 35(6), 8-11.

Bantel, K. A. and Jackson, S. E. (1989) 'Top management and innovations in banking: Does the composition of the top team make a difference?', *Strategic management journal,* 10(S1), 107-124.

Bargshady, G., Alipanah, F., Abdulrazzaq, A. W. and Chukwunonso, F. (2014) 'Business Inteligence Technology Implimentation Readiness Factors', *Jurnal Teknologi,* 68(3).

Barki, H. and Hartwick, J. (1989) 'Rethinking the concept of user involvement', *MIS quarterly*, 53-63.

Barki, H., Rivard, S. and Talbot, J. (2001) 'An Integrative Contingency Model of Software Project Risk Management', *Journal of management information systems,* 17(4), 37-69.

Baroudi, J. J., Olson, M. H. and Ives, B. (1986) 'An empirical study of the impact of user involvement on system usage and information satisfaction', *Communications of the ACM,* 29(3), 232-238.

Barrett, P. (2007) 'Structural equation modelling: Adjudging model fit', *Personality and Individual differences,* 42(5), 815-824.

Bell, E., Bryman, A. and Harley, B. (2018) *Business research methods,* 5th ed., Oxford: Oxford university press.

Bentler, P. M. and Bonett, D. G. (1980) 'Significance tests and goodness of fit in the analysis of covariance structures', *Psychological bulletin,* 88(3), 588.

Bernard, H. R. (2013) *Social research methods : qualitative and quantitative methods,* Thousand Oaks, Calif.: SAGE Publications.

Beynon-Davies, P., Owens, I. and Williams, M. D. (2004) 'Information systems evaluation and the information systems development process', *Journal of Enterprise Information Management*.

Bhattacherjee, A. (2001) 'Understanding information systems continuance: an expectation-confirmation model', *MIS quarterly*, 351-370.

Blunch, N. (2012) *Introduction to structural equation modeling using IBM SPSS statistics and AMOS,* 2nd ed.*,* London: Sage.

Bolam, F. C., Grainger, M. J., Mengersen, K. L., Stewart, G. B., Sutherland, W. J., Runge, M. C. and McGowan, P. J. (2019) 'Using the Value of Information to improve conservation decision making', *Biological Reviews,* 94(2), 629-647.

Bollen, K. A. and Long, J. S. (1993) *Testing structural equation models,* Sage.

Boonsiritomachai, W., McGrath, M. and Burgess, S. (2014) *A research framework for the adoption of Business Intelligence by Small and Medium-sized enterprises,* translated by SEAANZ, 1-22.

Bostrom, R. P. and Heinen, J. S. (1977) 'MIS problems and failures: A socio-technical perspective. Part I: The causes', *MIS quarterly*, 17-32.

Boyton, J., Ayscough, P., Kaveri, D. and Chiong, R. (2015) 'Suboptimal business intelligence implementations: understanding and addressing the problems', *Journal of Systems and Information Technology,* 17(3), 307-320.

Bracken, S. (2010) 'Discussing the Importance of Ontology and Epistemology Awareness in Practitioner Research', *Worcester Journal of learning and teaching,* (4).

Brown, D. H. and Thompson, S. (2011) 'Priorities, policies and practice of e-government in a developing country context: ICT infrastructure and diffusion in Jamaica', *European Journal of Information Systems,* 20(3), 329-342.

Brown, R., Butow, P., Wilson-Genderson, M., Bernhard, J., Ribi, K. and Juraskova, I. (2012) 'Meeting the decision-making preferences of patients with breast cancer in oncology consultations: impact on decision-related outcomes', *Journal of clinical oncology,* 30(8), 857-862.

Brown, T. A. (2015) *Confirmatory factor analysis for applied research,* Guilford publications.

Browne, M. W. and Cudeck, R. (1992) 'Alternative ways of assessing model fit', *Sociological methods and research,* 21(2), 230-258.

Bryceson, D. F., Fisher, E., Jønsson, J. B. and Mwaipopo, R. (2013) *Mining and social transformation in Africa: Mineralizing and democratizing trends in artisanal production,* Routledge.

Bryman, A. (2016) *Social research methods,* 5th ed.*,* Oxford: Oxford university press.

Burton-Jones, A. and Hubona, G. S. (2005) 'Individual differences and usage behavior: revisiting a technology acceptance model assumption', *ACM SIGMIS Database: the DATABASE for Advances in Information Systems,* 36(2), 58-77.

Burton-Jones, A., Recker, J., Indulska, M., Green, P. and Weber, R. (2017) 'Assessing representation theory with a framework for pursuing success and failure', *MIS quarterly,* 41(4), 1307-1333.

Byrne, B. M. (2004) 'Testing for multigroup invariance using AMOS graphics: A road less traveled', *Structural equation modeling,* 11(2), 272-300.

Byrne, B. M. (2008) 'Testing for multigroup equivalence of a measuring instrument: A walk through the process', *Psicothema,* 20(4), 872-882.

Byrne, B. M. (2016) *Structural equation modeling with AMOS : basic concepts, applications, and programming,* 3rd ed.*,* New York: Routledge.

Caldeira, M. M. and Ward, J. M. (2002) 'Understanding the successful adoption and use of IS/IT in SMEs: an explanation from Portuguese manufacturing industries', *Information Systems Journal,* 12(2), 121-152.

Caldwell, B. (2015) *Beyond positivism,* London and New York: Routledge.

Campion, M. A., Medsker, G. J. and Higgs, A. C. (1993) 'Relations between work group characteristics and effectiveness: Implications for designing effective work groups', *Personnel psychology,* 46(4), 823-847.

Cardella, E. (2012) 'Learning to make better strategic decisions', *Journal of Economic Behavior and Organization,* 84(1), 382-392.

Carmeli, A., Tishler, A. and Edmondson, A. C. (2012) 'CEO relational leadership and strategic decision quality in top management teams: The role of team trust and learning from failure', *Strategic Organization,* 10(1), 31-54.

Carter, S. M. and Little, M. (2007) 'Justifying knowledge, justifying method, taking action: Epistemologies, methodologies, and methods in qualitative research', *Qualitative health research,* 17(10), 1316-1328.

Chamoni, P. and Gluchowski, P. (2004) 'Integrationstrends bei Business-Intelligence-Systemen', *Wirtschaftsinformatik,* 46(2), 119-128.

Chatterjee, S., Chakraborty, S., Sarker, S., Sarker, S. and Lau, F. Y. (2009) 'Examining the success factors for mobile work in healthcare: a deductive study', *Decision support systems,* 46(3), 620-633.

Chau, P. Y. and Hu, P. J. (2002) 'Examining a model of information technology acceptance by individual professionals: An exploratory study', *Journal of management information systems,* 18(4), 191-229.

Chen, H., Chiang, R. H. and Storey, V. C. (2012) 'Business intelligence and analytics: From big data to big impact', *MIS quarterly*, 1165-1188.

Chen, L.-d. and Nath, R. (2008) 'Determinants of mobile payments: an empirical analysis', *Journal of International Technology and Information Management,* 17(1), 2.

Chewning Jr, E. G. and Harrell, A. M. (1990) 'The effect of information load on decision makers' cue utilization levels and decision quality in a financial distress decision task', *Accounting, Organizations and Society,* 15(6), 527-542.

Chiasson, M. W. and Davidson, E. (2005) 'Taking industry seriously in information systems research', *MIS quarterly*, 591-605.

Chin, W. W. and Todd, P. A. (1995) 'On the use, usefulness, and ease of use of structural equation modeling in MIS research: a note of caution', *MIS quarterly*, 237-246.

Cho, J.-H., Xu, S., Hurley, P. M., Mackay, M., Benjamin, T. and Beaumont, M. (2019) 'Stram: Measuring the trustworthiness of computer-based systems', *ACM Computing Surveys (CSUR),* 51(6), 1-47.

Choy, L. T. (2014) 'The strengths and weaknesses of research methodology: Comparison and complimentary between qualitative and quantitative approaches', *IOSR Journal of Humanities and Social Science,* 19(4), 99-104.

Churchill Jr, G. A. (1979) 'A paradigm for developing better measures of marketing constructs', *Journal of Marketing Research*, 64-73.

Clark, T. D., Jones, M. C. and Armstrong, C. P. (2007) 'The dynamic structure of management support systems: theory development, research focus, and direction', *MIS quarterly,* 31(3), 579-615.

Claver, E., Llopis, J., González, M. R. and Gasco, J. L. (2001) 'The performance of information systems through organizational culture', *Information Technology and People*.

Cohen, M. D. and March, J. G. (1974) 'Leadership and ambiguity: The American college president'.

Collis, J. and Hussey, R. (2014) *Business research : a practical guide for undergraduate and postgraduate students,* Basingstoke : Hampshire: Palgrave Macmillan.

Cooper, D. R. and Schindler, P. S. (2014) *Business Research Methods,* New York, N.Y.: McGraw-Hill/Irwin.

Cooper, R. B. and Zmud, R. W. (1990) 'Information technology implementation research: a technological diffusion approach', *Management science,* 36(2), 123-139.

Cosic, R., Shanks, G. and Maynard, S. B. (2015) 'A business analytics capability framework', *Australasian Journal of Information Systems,* 19.

Cox, J. M. and Davison, A. (2005) 'The visual analogue scale as a tool for self-reporting of subjective phenomena in the medical radiation sciences', *Radiographer,* 52(1), 22-24.

Creswell, J. W. and Creswell, J. D. (2017) *Research design: Qualitative, quantitative, and mixed methods approaches,* 5th ed., London: Sage.

Creswell, J. W. and Plano Clark, V. L. (2018) *Designing and conducting mixed methods research,* Los Angeles: SAGE.

Crotty, M. (1998) *The foundations of social research meaning and perspective in the research process,* London: Sage.

Cyr, D., Head, M., Larios, H. and Pan, B. (2009) 'Exploring human images in website design: A multi-method approach', *MIS quarterly,* 33(3), 539-566.

Davenport, T. and Harris, J. (2007) 'Competing on analytics: The new science of winning. Boston: Harvard Business School Press, Boston Massachusetts. A short description is retrieved at March 20, 2016',

Davenport, T. H. (2006) 'Competing on analytics', *Harvard business review,* 84(1), 98.

Davenport, T. H., Harris, J. G. and Morison, R. (2010) *Analytics at work: Smarter decisions, better results,* Harvard Business Press.

Davis, F. D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS quarterly*, 319-340.

Davis, W. S. and Yen, D. C. (2018) *The information system consultant's handbook: Systems analysis and design,* CRC press.

Dawson, L. and Van Belle, J.-P. (2013) 'Critical success factors for business intelligence in the South African financial services sector: original research', *South African Journal of Information Management,* 15(1), 1-12.

Dean Jr, J. W. and Sharfman, M. P. (1993) 'Procedural rationality in the strategic decision-making process', *Journal of management Studies,* 30(4), 587-610.

Delen, D. and Demirkan, H. (2013) 'Data, information and analytics as services',

DeLone, W. H. and McLean, E. R. (1992) 'Information systems success: The quest for the dependent variable', *Information Systems Research,* 3(1), 60-95.

DeLone, W. H. and McLean, E. R. (2002) *Information systems success revisited,* translated by IEEE, 2966-2976.

Delone, W. H. and 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.

DeSanctis, G. and Poole, M. S. (1994) 'Capturing the complexity in advanced technology use: Adaptive structuration theory', *Organization science,* 5(2), 121-147.

DeVellis, R. F. (2016) *Scale development: Theory and applications,* 4th ed.*,* London: Sage.

Doll, W. J. and Torkzadeh, G. (1988) 'The measurement of end-user computing satisfaction', *MIS quarterly*, 259-274.

Doll, W. J. and Torkzadeh, G. (1991) 'The measurement of end-user computing satisfaction: theoretical and methodological issues', *MIS quarterly*, 5-10.

Dooley, P. (2015) 'An Empirical Development of Critical Value Factors for System Quality and Information Quality in Business Intelligence Systems Implementations'.

Dooley, P., Levy, Y., Hackney, R. and Parrish, J. (2017) 'Critical value factors in business intelligence systems implementations'.

Dutton, W., Guerra, G. A., Zizzo, D. J. and Peltu, M. (2005) 'The cyber trust tension in E-government: Balancing identity, privacy, security', *Information Polity,* 10(1, 2), 13-23.

Easterby-Smith, M., Thorpe, R., Jackson, P. R. and Jaspersen, L. J. (2018) *Management and business research,* 6th ed.*,* Los Angeles: Sage.

Eckerson, W. (2003) 'Smart companies in the 21st century: The secrets of creating successful business intelligence solutions. TDWI The Data Warehousing Institute Report Series, 1-35',

Eckerson, W. W. (2005) 'The keys to enterprise business intelligence: Critical success factors', *The Data Warehousing Institute. Retrieved October,* 2, 2011.

Edwards, A. and Elwyn, G. (2009) *Shared decision-making in health care: Achieving evidence-based patient choice,* Oxford University Press.

El-Adaileh, N. A. and Foster, S. (2019) 'Successful business intelligence implementation: a systematic literature review', *Journal of Work-Applied Management*.

Elsheikh, Y. and Hijjawi, M. (2016) 'A Replicated Assessment of the Critical Success Factors for the Adoption of Mobile Government Services : The Case of Jordan', *International Journal of Computer Science and Information Technology,* 8(4), 41-53.

Emam, A. Z. (2013) *Critical success factors model for business intelligent over ERP cloud,* translated by IEEE, 1-5.

Energ and Minerals Regulatory Commissiom (2018) *Annual Report 2018*, Amman: Energ and Minerals Regulatory Commissiom.

Estabrook, R. and Neale, M. (2013) 'A comparison of factor score estimation methods in the presence of missing data: Reliability and an application to nicotine dependence', *Multivariate behavioral research,* 48(1), 1-27.

Etezadi-Amoli, J. and Farhoomand, A. F. (1996) 'A structural model of end user computing satisfaction and user performance', *Information and Management,* 30(2), 65-73.

Fedouaki, F., Okar, C. and Alami, S. E. (2013) 'A maturity model for Business Intelligence System project in Small and Medium-sized Enterprises: An empirical investigation', *IJCSI International Journal of Computer Science Issues,* 10(6), 61-69.

Field, A. (2017) *Discovering statistics using IBM SPSS statistics: North American edition,* 5th ed.*,* London: Sage.

Filieri, R. and McLeay, F. (2014) 'E-WOM and accommodation: An analysis of the factors that influence travelers’ adoption of information from online reviews', *Journal of Travel Research,* 53(1), 44-57.

Fink, L., Yogev, N. and Even, A. (2017) 'Business intelligence and organizational learning: An empirical investigation of value creation processes', *Information and Management,* 54(1), 38-56.

Fishbein, M. and Ajzen, I. (1975) 'Intention and Behavior: An introduction to theory and research',

Fleck, J. (1994) 'Learning by trying: the implementation of configurational technology', *Research policy,* 23(6), 637-652.

Fogg, B. J. and Tseng, H. (1999) *The elements of computer credibility,* translated by 80-87.

Fourati-Jamoussi, F. and Niamba, C. N. (2016) 'An evaluation of business intelligence tools: a cluster analysis of users’ perceptions', *Journal of Intelligence Studies in Business,* 6(1).

Fuller, C. M., Simmering, M. J., Atinc, G., Atinc, Y. and Babin, B. J. (2016) 'Common methods variance detection in business research', *Journal of business research,* 69(8), 3192-3198.

Gaardboe, R. and Svarre, T. (2018) 'Business intelligence success factors: a literature review', *Journal of Information Technology Management,* 29(1), 1-15.

Gable, G., Sedera, D. and Chan, T. (2003) 'Enterprise systems success: a measurement model', *ICIS 2003 Proceedings*, 48.

Gable, G. G., Sedera, D. and Chan, T. (2008) 'Re-conceptualizing information system success: The IS-impact measurement model', *Journal of the Association for Information Systems,* 9(7), 18.

Galbraith, J. R. (1974) 'Organization design: An information processing view', *Interfaces,* 4(3), 28-36.

García, J. M. V. and Pinzón, B. H. D. (2017) 'Key success factors to business intelligence solution implementation', *Journal of Intelligence Studies in Business,* 7(1).

Garrity, E. J. and Sanders, G. L. (1998) *Information systems success measurement,* Igi Global.

Gartner (2019) *Market Share: Analytics and Business Intelligence, Worldwide, 2018*, Gartner Research.

Gaskin, J. (2016) 'ValidityMaster, Stats Tools Package', [online], available: http://statwiki.kolobkreations.com [Accessed March,11 2019].

Gasser, L. (1986) 'The integration of computing and routine work', *ACM Transactions on Information Systems (TOIS),* 4(3), 205-225.

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

Gefen, D., Rigdon, E. E. and Straub, D. (2011) 'Editor's comments: an update and extension to SEM guidelines for administrative and social science research', *MIS quarterly*, iii-xiv.

Gefen, D., Straub, D. and Boudreau, M.-C. (2000) 'Structural equation modeling and regression: Guidelines for research practice', *Communications of the association for information systems,* 4(1), 7.

Giddens, A. (1984) *The constitution of society: Outline of the theory of structuration,* Univ of California Press.

Gill, J. and Johnson, P. (2010) *Research methods for managers,* Los Angeles: Sage.

Ginzberg, M. J. (1981) 'Early diagnosis of MIS implementation failure: promising results and unanswered questions', *Management science,* 27(4), 459-478.

Glancy, F. H. and Yadav, S. B. (2011) 'Business intelligence conceptual model', *International Journal of Business Intelligence Research (IJBIR),* 2(2), 48-66.

Global Entrepreneurship and Development Index (2018) *Global Innovation Index 2018 rankings*, Washington, DC: The Global Entrepreneurship and Development Institute.

Golfarelli, M., Rizzi, S. and Cella, I. (2004) *Beyond data warehousing: what's next in business intelligence?,* translated by 1-6.

Goodhue, D. L. and Thompson, R. L. (1995) 'Task-technology fit and individual performance', *MIS quarterly*, 213-236.

Gorla, N., Somers, T. M. and Wong, B. (2010) 'Organizational impact of system quality, information quality, and service quality', *The Journal of Strategic Information Systems,* 19(3), 207-228.

Grand View Research (2019) *Business Intelligence Software Market Size, Share and Trends Analysis Report By Technology, By Function (Executive Management, Finance), By Tool, By Deployment, By Enterprise Size, By End Use, By Region, And Segment Forecasts, 2019 - 2025*, San Francisco: Grand View Research.

Grandon, E. E. and Pearson, J. M. (2004) 'Electronic commerce adoption: an empirical study of small and medium US businesses', *Information and Management,* 42(1), 197-216.

Gratton, S. (2012) 'BI 3.0 The Journey to Business Intelligence. What does it mean', *Capgemini Worldwide. Haettu,* 22, 2019.

Grimsley, M. and Meehan, A. (2007) 'e-Government information systems: Evaluation-led design for public value and client trust', *European Journal of Information Systems,* 16(2), 134-148.

Grover, V., Jeong, S. R., Kettinger, W. J. and Teng, J. T. C. (1995) 'The Implementation of Business Process Reengineering', *Journal of management information systems,* 12(1), 109-144.

Grublješič, T. and Jaklič, J. (2015) 'Business Intelligence Acceptance: The Prominence of Organizational Factors', *Information Systems Management,* 32(4), 299-315.

Guimaraes, T. and Igbaria, M. (1997) 'Client/server system success: Exploring the human side', *Decision Sciences,* 28(4), 851-876.

Guimaraes, T., Staples, D. S. and Mckeen, J. D. (2003) 'Empirically testing some main user-related factors for systems development quality', *Quality Management Journal,* 10(4), 39-50.

Guimaraes, T., Yoon, Y. and Clevenson, A. (1996) 'Factors important to expert systems success', *Information and Management,* 30(3), 119-130.

Gurjar, Y. S. and Rathore, V. S. (2013) 'Cloud business intelligence–is what business need today', *International Journal of Recent Technology and Engineering,* 1(6), 81-86.

Gurnsey, F. N. (2017) *Statistics for research in psychology : a modern approach using estimation,* Los Angeles: Sage.

Hackbarth, G., Grover, V. and Mun, Y. Y. (2003) 'Computer playfulness and anxiety: positive and negative mediators of the system experience effect on perceived ease of use', *Information and Management,* 40(3), 221-232.

Hackney, R., Dooley, P., Levvy, Y. and Parrish, J. (2015) 'Critical value factors in business intelligence systems implementation success: An empirical analysis of system and information quality'.

Hahn, A., Austing, S. G. and Strickmann, J. (2008) 'Ontology based metrics–applying business intelligence on PLM', *International Journal of Product Lifecycle Management,* 3(4), 308-318.

Hair, J., Black, W., Anderson, R. and Babin, B. (2018) *Multivariate Data Analysis* 8th ed.*,* Andover: Cengage Learning EMEA

Håkansson, A. (2013) *Portal of research methods and methodologies for research projects and degree projects,* translated by Las Vegas USA: CSREA Press USA, 67-73.

Harding, J., Shahbaz, M. and Kusiak, A. (2006) 'Data mining in manufacturing: a review'.

Harris, M. A. and Weistroffer, H. R. (2009) 'A new look at the relationship between user involvement in systems development and system success', *Communications of the association for information systems,* 24(1), 42.

Hartwick, J. and Barki, H. (1994) 'Explaining the role of user participation in information system use', *Management science,* 40(4), 440-465.

Hasan, H. M., Lotfollah, F. and Negar, M. (2012) 'Comprehensive Model of Business Intelligence: a Case Study of Nano's Companies', *Indian Journal of Science and Technology,* 5(6), 2851-2859.

Hasan, L. and Abuelrub, E. (2008) 'Assessing the quality of Web Sites', *INFOCOMP,* 7(4), 11-20.

Hatta, M., Natasha, N., Miskon, S. and Syed Abdullah, N. (2017) *Business Intelligence System Adoption Model for SMEs,* translated by 192.

Hawking, P. and Sellitto, C. (2010) *Business Intelligence (BI) critical success factors,* translated by 1-3.

Hayes, A. F. (2009) 'Beyond Baron and Kenny: Statistical mediation analysis in the new millennium', *Communication monographs,* 76(4), 408-420.

Heeks, R. (2017) *Information and communication technology for development (ICT4D),* Routledge.

Hendrickson, A. R., Glorfeld, K. and Cronan, T. P. (1994) 'On the repeated test-retest reliability of the end-user computing satisfaction instrument: A comment', *Decision Sciences,* 25(4), 655-665.

Heng, M. S., Trauth, E. M. and Fischer, S. J. (1999) 'Organisational champions of IT innovation', *Accounting, Management and Information Technologies,* 9(3), 193-222.

Herrmann, T., Hoffmann, M., Kunau, G. and Loser, K.-U. (2004) 'A modelling method for the development of groupware applications as socio-technical systems', *Behaviour and Information Technology,* 23(2), 119-135.

Heyler, S. G., Armenakis, A. A., Walker, A. G. and Collier, D. Y. (2016) 'A qualitative study investigating the ethical decision making process: A proposed model', *The Leadership Quarterly,* 27(5), 788-801.

Ho, T.-H., Lim, N., Reza, S. and Xia, X. (2017) 'OM forum—Causal inference models in operations management', *Manufacturing and Service Operations Management,* 19(4), 509-525.

Holden, M. T. and Lynch, P. (2004) 'Choosing the appropriate methodology: Understanding research philosophy', *The marketing review,* 4(4), 397-409.

Hooper, D., Coughlan, J. and Mullen, M. R. (2008) 'Structural equation modelling: Guidelines for determining model fit', *Electronic journal of business research methods,* 6(1), 53-60.

Horsburgh, S., Goldfinch, S. and Gauld, R. (2011) 'Is public trust in government associated with trust in e-government?', *Social Science Computer Review,* 29(2), 232-241.

Hostmann, B. (2007) 'BI competency centres: bringing intelligence to the business', *Business Performance Management,* 5(4), 4-10.

Howard, R. and Abbas, A. (2016) 'Foundations of Decision Analysis, global edition', *Harlow, England: Pearson Education Limited*.

Howell, J. M. and Higgins, C. A. (1990) 'Champions of technological innovation', *Administrative science quarterly*, 317-341.

Howson, C. (2007) *Successful business intelligence,* Tata McGraw-Hill Education.

Hoyle, R. H. (1995) *Structural equation modeling: Concepts, issues, and applications,* Sage.

Hu, L. t. and Bentler, P. M. (1999) 'Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives', *Structural equation modeling: a multidisciplinary journal,* 6(1), 1-55.

Huang, S. M., Chang, I. C., Li, S. H. and Lin, M. T. (2004) 'Assessing risk in ERP projects: identify and prioritize the factors', *Industrial Management and Data Systems*.

Hughes, J. A. and Sharrock, W. W. (2016) *The philosophy of social research,* 3rd ed., London: Routledge.

Hung, S.-Y., Huang, Y.-W., Lin, C.-C., Chen, K. and Tarn, J. M. (2016) *Factors Influencing Business Intelligence Systems Implementation Success in the Enterprises,* translated by 297.

Hung, S.-Y., Hung, W.-H., Tsai, C.-A. and Jiang, S.-C. (2010) 'Critical factors of hospital adoption on CRM system: Organizational and information system perspectives', *Decision support systems,* 48(4), 592-603.

Hwang, M. I. and Xu, H. (2008) 'A structural model of data warehousing success', *Journal of Computer Information Systems,* 49(1), 48-56.

Igbaria, M. and Greenhaus, J. H. (1992) 'Determinants of MIS employees' turnover intentions: a structural equation model', *Communications of the ACM,* 35(2), 34-49.

Igbaria, M., Zinatelli, N., Cragg, P. and Cavaye, A. L. M. (1997) 'Personal Computing Acceptance Factors in Small Firms: A Structural Equation Model', *MIS quarterly,* 21(3), 279-305.

Iivari, J. (2005) 'An empirical test of the DeLone-McLean model of information system success', *ACM SIGMIS Database: the DATABASE for Advances in Information Systems,* 36(2), 8-27.

Ika, L. A., Diallo, A. and Thuillier, D. (2012) 'Critical success factors for World Bank projects: An empirical investigation', *International Journal of Project Management,* 30(1), 105-116.

Intaj (2017) *Jordan ICT and ITES Sector Statistics 2017*, Amman: Information and Communications Technology Association.

International Data Corporation (2018) *Worldwide Big Data and Analytics Software Forecast, 2018–2022*, Framingham: International Data Corporation.

Işık, Ö., Jones, M. C. and Sidorova, A. (2013) 'Business intelligence success: The roles of BI capabilities and decision environments', *Information and Management,* 50(1), 13-23.

Ives, B. and Olson, M. H. (1984) 'User involvement and MIS success: A review of research', *Management science,* 30(5), 586-603.

Jacoby, J. (1977) 'Information load and decision quality: Some contested issues', *Journal of Marketing Research,* 14(4), 569-573.

Janssen, M., van der Voort, H. and Wahyudi, A. (2017) 'Factors influencing big data decision-making quality', *Journal of business research,* 70, 338-345.

Jarvenpaa, S. L. and Ives, B. (1991) 'Executive involvement and participation in the management of information technology', *MIS quarterly*, 205-227.

Jarvis, C. B., MacKenzie, S. B. and Podsakoff, P. M. (2003) 'A critical review of construct indicators and measurement model misspecification in marketing and consumer research', *Journal of consumer research,* 30(2), 199-218.

Jason, L. and Glenwick, D. (2016) *Handbook of methodological approaches to community-based research : qualitative, quantitative, and mixed methods*.

Jeyaraj, A. (2019) 'Variation in the effect of system usage and individual impact: A meta-regression of empirical findings', *Information and Management*, 103242.

Jonker, J. and Pennink, B. (2014) *The Essence of Research Methodology A Concise Guide for Master and PhD Students in Management Science,* Berlin: Springer Berlin.

Jordan Department of Statistics (2018) *Jordan Statistical Yearbook 2018*, Jordan: The Department of Statistics

Jordan Phosphate Mines Company (2018) *Annual Report 2018*, Amman: Jordan Phosphate Mines Company.

Jugdev, K. and Müller, R. (2005) 'A retrospective look at our evolving understanding of project success', *Project management journal,* 36(4), 19-31.

Kahneman, D. and Tversky, A. (2013) 'Choices, values, and frames' in *Handbook of the fundamentals of financial decision making: Part I*, World Scientific, 269-278.

Kaltoft, M., Cunich, M., Salkeld, G. and Dowie, J. (2014) 'Assessing decision quality in patient-centred care requires a preference-sensitive measure', *Journal of health services research and policy,* 19(2), 110-117.

Kappelman, L., Johnson, V., Torres, R., Maurer, C. and McLean, E. (2019) 'A study of information systems issues, practices, and leadership in Europe', *European Journal of Information Systems,* 28(1), 26-42.

Karahanna, E., Straub, D. W. and Chervany, N. L. (1999) 'Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs', *MIS quarterly*, 183-213.

Karimi, J., Somers, T. M. and Bhattacherjee, A. (2007) 'The Role of Information Systems Resources in ERP Capability Building and Business Process Outcomes', *Journal of management information systems,* 24(2), 221-260.

Kariv, S. and Silverman, D. (2013) 'An old measure of decision-making quality sheds new light on paternalism', *Journal of Institutional and Theoretical Economics (JITE)/Zeitschrift für die gesamte Staatswissenschaft*, 29-44.

Karsten, R., Mitra, A. and Schmidt, D. (2012) 'Computer self-efficacy: A meta-analysis', *Journal of Organizational and End User Computing (JOEUC),* 24(4), 54-80.

Kaul, P. and Joslin, R. (2018) 'Understanding PMO Success',

Kayworth, T. R. and Leidner, D. E. (2001) 'Leadership Effectiveness in Global Virtual Teams', *Journal of management information systems,* 18(3), 7-40.

Kearns, G. S. and Sabherwal, R. (2006) 'Strategic alignment between business and information technology: a knowledge-based view of behaviors, outcome, and consequences', *Journal of management information systems,* 23(3), 129-162.

Keeney, R. L. (2004) 'Framing public policy decisions', *International Journal of Technology, Policy and Management,* 4(2), 95-115.

Keisler, J. M. and Noonan, P. S. (2012) 'Communicating analytic results: A tutorial for decision consultants', *Decision Analysis,* 9(3), 274-292.

Kerschner, C. and Ehlers, M.-H. (2016) 'A framework of attitudes towards technology in theory and practice', *Ecological Economics,* 126, 139-151.

Kfouri, G. and Skyrius, R. (2016) 'Factors influencing the implementation of business intelligence among small and medium enterprises in Lebanon', *Informacijos mokslai,* 76(76), 96-110.

Kim, S. S. (2009) 'The integrative framework of technology use: An extension and test', *MIS quarterly,* 33(3), 513-537.

Klakegg, O. J. (2016) 'Ontology and epistemology' in *Designs, Methods and Practices for Research of Project Management*, Routledge, 87-96.

Klein, K. J., Conn, A. B. and Speer Sorra, J. (2001) 'Implementing Computerized Technology: An Organizational Analysis', *Journal of Applied Psychology,* 86(5), 811-824.

Kline, R. B. (2015) *Principles and practice of structural equation modeling,* 4th ed., New York: Guilford publications.

Klopping, I. M. and McKinney, E. (2004) 'Extending the technology acceptance model and the task-technology fit model to consumer e-commerce', *Information Technology, Learning and Performance Journal,* 22(1).

Kopeikina, L. (2005) 'Decisions, decisions', *FORTUNE,* 152(2), 14-14.

Kræmmergaard, P. and Rose, J. (2002) 'Managerial competences for ERP journeys', *Information systems frontiers,* 4(2), 199-211.

Kucukaltan, B., Irani, Z. and Aktas, E. (2016) 'A decision support model for identification and prioritization of key performance indicators in the logistics industry', *Computers in human behavior,* 65, 346-358.

Kulkarni, C., Wei, K. P., Le, H., Chia, D., Papadopoulos, K., Cheng, J., Koller, D. and Klemmer, S. R. (2013) 'Peer and self assessment in massive online classes', *ACM Transactions on Computer-Human Interaction (TOCHI),* 20(6), 1-31.

Kwon, T. H. and Zmud, R. W. (1987) 'Unifying the fragmented models of information systems implementation' in *Critical issues in information systems research*, 227-251.

Land, F. (1985) 'Is an information theory enough?', *The Computer Journal,* 28(3), 211-215.

Langer, E. J. (1975) 'The illusion of control', *Journal of personality and social psychology,* 32(2), 311.

Lapointe, L. and Rivard, S. (2007) 'A triple take on information system implementation', *Organization science,* 18(1), 89-107.

Lassila, K. S. and Brancheau, J. C. (1999) 'Adoption and utilization of commercial software packages: Exploring utilization equilibria, transitions, triggers, and tracks', *Journal of management information systems,* 16(2), 63-90.

Laudon, K. C. and Laudon, J. P. (2017) *Management information systems: managing the digital firm,* 15th ed.*,* Essex: Pearson.

Lautenbach, P., Johnston, K. and 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.

Law, C. C. and Ngai, E. W. (2007) 'ERP systems adoption: An exploratory study of the organizational factors and impacts of ERP success', *Information and Management,* 44(4), 418-432.

Lazar, J., Feng, J. H. and Hochheiser, H. (2017) *Research methods in human-computer interaction,* Morgan Kaufmann.

Lee, B., Alexander, M., Hawkes, B., Lynham, T., Stocks, B. and Englefield, P. (2002) 'Information systems in support of wildland fire management decision making in Canada', *Computers and Electronics in Agriculture,* 37(1-3), 185-198.

Lee, G. and Xia, W. (2010) 'Toward agile: an integrated analysis of quantitative and qualitative field data on software development agility', *MIS quarterly,* 34(1), 87-114.

Lee, J. and Choi, H. (2017) 'What affects learner's higher-order thinking in technology-enhanced learning environments? The effects of learner factors', *Computers and Education,* 115, 143-152.

Lee, K. C., Kang, I. and McKnight, D. H. (2007) 'Transfer from offline trust to key online perceptions: an empirical study', *IEEE transactions on Engineering Management,* 54(4), 729-741.

Leslie, L. and Caldwell, J. S. (2016) *Qualitative reading inventory,* Pearson.

Li, X., Hess, T. J. and Valacich, J. S. (2008) 'Why do we trust new technology? A study of initial trust formation with organizational information systems', *The Journal of Strategic Information Systems,* 17(1), 39-71.

Library of Congress (2006) *Country Profile: Jordan, September 2006* washington dc: Federal Research Division.

Liebowitz, J. (2006) *Strategic intelligence: business intelligence, competitive intelligence, and knowledge management,* Auerbach Publications.

Lim, K. H., Benbasat, I. and Ward, L. M. (2000) 'The Role of Multimedia in Changing First Impression Bias', *Information Systems Research,* 11(2), 115-136.

Lipshitz, R. and Strauss, O. (1997) 'Coping with uncertainty: A naturalistic decision-making analysis', *Organizational behavior and human decision processes,* 69(2), 149-163.

Liu, B. Q. and Goodhue, D. L. (2012) 'Two Worlds of Trust for Potential E-Commerce Users: Humans as Cognitive Misers', *Information Systems Research,* 23(4), 1246-1262.

Liu, I. L., Cheung, C. M. and Lee, M. K. (2016) 'User satisfaction with microblogging: Information dissemination versus social networking', *Journal of the Association for Information Science and Technology,* 67(1), 56-70.

Liu, X. (2016) 'Fitting Proportional Odds Models for Complex Sample Survey Data with SAS, IBM SPSS, Stata, and R', *General Linear Model Journal,* 42(2), 1-39.

Loh, T. C. and Koh, S. (2004) 'Critical elements for a successful enterprise resource planning implementation in small-and medium-sized enterprises', *International Journal of Production Research,* 42(17), 3433-3455.

Loshin, D. (2003) *Business intelligence: getting onboard with emerging IT,* Morgan Kaufmann Publishers.

Lucas, H. C. and Nielsen, N. R. (1980) 'The impact of the mode of information presentation on learning and performance', *Management science,* 26(10), 982-993.

Luhn, H. P. (1958) 'A business intelligence system', *IBM Journal of Research and Development,* 2(4), 314-319.

Lyytinen, K. and Newman, M. (2006) 'Punctuated equilibrium, process models and information system development and change: towards a socio-technical process analysis', *Sprouts: Working papers on information environments, systems and organizations,* 6(1), 1-48.

MacKenzie, S. B., Podsakoff, P. M. and Podsakoff, N. P. (2011) 'Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques', *MIS quarterly,* 35(2), 293-334.

MacKinnon, D. P., Coxe, S. and Baraldi, A. N. (2012) 'Guidelines for the investigation of mediating variables in business research', *Journal of Business and Psychology,* 27(1), 1-14.

MacKinnon, D. P. and Pirlott, A. G. (2015) 'Statistical approaches for enhancing causal interpretation of the M to Y relation in mediation analysis', *Personality and Social Psychology Review,* 19(1), 30-43.

Mahoney, M. J. (1992) 'Scientific psychology and radical behaviorism: Important distinctions based in scientism and objectivism'.

Malhotra, N. K., Kim, S. S. and Patil, A. (2006) 'Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research', *Management science,* 52(12), 1865-1883.

Malhotra, Y. and Galletta, D. (2005) 'A multidimensional commitment model of volitional systems adoption and usage behavior', *Journal of management information systems,* 22(1), 117-151.

Malkawi, N. M. (2018) 'How to Improve Decision Making Process through Decision Support Systems and Business Intelligence: Evidence from Jordan University Hospital', *Journal of Economic and Management Perspectives,* 12(2), 255-265.

Mandal, P. and Gunasekaran, A. (2003) 'Issues in implementing ERP: A case study', *European Journal of Operational Research,* 146(2), 274-283.

Marino, A. and Eastman, W. (2017) 'Maximizing Value in Board Decisions: The Role of the Decision Quality Officer', *Rutgers Business Review,* 2(2).

Mathieu, J. E. and Taylor, S. R. (2006) 'Clarifying conditions and decision points for mediational type inferences in organizational behavior', *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior,* 27(8), 1031-1056.

Matsunaga, M. (2010) 'How to Factor-Analyze Your Data Right: Do's, Don'ts, and How-To's', *International journal of psychological research,* 3(1), 97-110.

May, T. and Williams, M. (2002) *An introduction to the philosophy of social research,* Routledge.

McAfee, A. (2002) 'The impact of enterprise information technology adoption on operational performance: An empirical investigation', *Production and operations management,* 11(1), 33-53.

McElroy, E. J., Marien, C., Meyers, J. J. and Irschick, D. J. (2007) 'Do displays send information about ornament structure and male quality in the ornate tree lizard, Urosaurus ornatus?', *Ethology,* 113(11), 1113-1122.

McEvoy, P. and Richards, D. (2006) 'A critical realist rationale for using a combination of quantitative and qualitative methods', *Journal of research in nursing,* 11(1), 66-78.

McGill, T., Hobbs, V. and Klobas, J. (2003) 'User developed applications and information systems success: A test of DeLone and McLean's model', *Information Resources Management Journal (IRMJ),* 16(1), 24-45.

McGill, T., Payne, C., Bennett, D., Carter, K., Chong, A., Hornby, G. and Lim, L. (2000) 'System quality, user satisfaction and end user development'.

McKinney, V., Yoon, K. and Zahedi, F. M. (2002) 'The measurement of web-customer satisfaction: An expectation and disconfirmation approach', *Information Systems Research,* 13(3), 296-315.

McKnight, D. H., Lankton, N. K., Nicolaou, A. and Price, J. (2017) 'Distinguishing the effects of B2B information quality, system quality, and service outcome quality on trust and distrust', *The Journal of Strategic Information Systems,* 26(2), 118-141.

Mesaros, P., Carnicky, S., Mandicak, T., Habinakova, M., Mackova, D. and Spisakova, M. (2016) 'Model of key success factors for Business Intelligence implementation', *Journal of Systems Integration,* 7(3), 3.

Meyer, M. (2000) 'Innovation roles: from souls of fire to devil's advocates', *The Journal of Business Communication (1973),* 37(4), 328-347.

Michie, S. G., Dooley, R. S. and Fryxell, G. E. (2006) 'Unified diversity in top-level teams', *International Journal of Organizational Analysis*.

Mintzberg, H. (1977) 'Policy as a field of management theory', *Academy of management review,* 2(1), 88-103.

Mir, F. A. and Pinnington, A. H. (2014) 'Exploring the value of project management: linking project management performance and project success', *International Journal of Project Management,* 32(2), 202-217.

Molla, A. and Licker, P. S. (2001) 'E-commerce systems success: An attempt to extend and respecify the Delone and MacLean model of IS success', *J. Electron. Commerce Res.,* 2(4), 131-141.

Moorman, R. H. (1993) 'The influence of cognitive and affective based job satisfaction measures on the relationship between satisfaction and organizational citizenship behavior', *Human relations,* 46(6), 759-776.

Moss, L. T. and Atre, S. (2003) *Business intelligence roadmap: the complete project lifecycle for decision-support applications,* Addison-Wesley Professional.

Mumford, E., Hirschheim, R., Fitzgerald, G. and Wood-Harper, T. (1985) *Research methods in information systems,* North-Holland Amsterdam et al.

Mungree, D., Rudra, A. and Morien, D. (2013) 'A framework for understanding the critical success factors of enterprise business intelligence implementation'.

Murray, G. and Crothers, C. (1989) 'Corporate Decision-Making: some New Zealand survey evidence', *Critical Sociology,* 16(2-3), 75-89.

Naderinejad, M., Jafar Tarokh, M. and Poorebrahimi, A. (2014) 'Recognition and Ranking Critical Success Factors of Business Intelligence in Hospitals - Case Study: Hasheminejad Hospital', *International Journal of Computer Science and Information Technology,* 6(2), 121-129.

Nah, F. F.-H. and Delgado, S. (2006) 'Critical success factors for enterprise resource planning implementation and upgrade', *Journal of Computer Information Systems,* 46(5), 99-113.

Nasab, S. S., Selamat, H. and Masrom, M. (2015) 'A Delphi study of the important factors for BI system implementation in the public sector organizations', *Jurnal Teknologi,* 77(19), 113-120.

Ndou, V. (2004) 'E–Government for developing countries: opportunities and challenges', *The electronic journal of information systems in developing countries,* 18(1), 1-24.

Negash, S. (2004) 'Business intelligence', *The communications of the Association for Information Systems,* 13(1), 54.

Nelson, R. R. and Cheney, P. H. (1987) 'Training end users: an exploratory study', *MIS quarterly*, 547-559.

Nelson, R. R., Todd, P. A. and Wixom, B. H. (2005) 'Antecedents of information and system quality: an empirical examination within the context of data warehousing', *Journal of management information systems,* 21(4), 199-235.

Nemec, R. (2012) 'The application of business intelligence 3.0 concept in the management of small and medium enterprises', *IT for Practice 2012*.

Newbold, P., Carlson, W. L. and Thorne, B. (2013) *Statistics for business and economics,* Essex, England: Pearson Education Limited.

Newell, M. W. and Grashina, M. N. (2004) *The Project Management : Question and Answer,* New York: AMACOM.

Nguyen, T. H., Newby, M. and Macaulay, M. J. (2015) 'Information technology adoption in small business: Confirmation of a proposed framework', *Journal of Small Business Management,* 53(1), 207-227.

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

Nitsch, V. and Glassen, T. (2015) *Investigating the effects of robot behavior and attitude towards technology on social human-robot interactions,* translated by IEEE, 535-540.

Nunnally, J. C. and Bernstein, I. H. (1994) 'Psychological theory', *New York, NY: MacGraw-Hill*.

Nutt, P. C. (2011) 'Making decision-making research matter: some issues and remedies', *Management Research Review*.

Olbrich, S., Poppelbuß, J. and Niehaves, B. (2012) *Critical contextual success factors for business intelligence: A Delphi study on their relevance, variability, and controllability,* translated by IEEE, 4148-4157.

Olszak, C. M. (2016) 'Toward better understanding and use of Business Intelligence in organizations', *Information Systems Management,* 33(2), 105-123.

Olszak, C. M. and Ziemba, E. (2007) 'Approach to building and implementing business intelligence systems', *Interdisciplinary Journal of Information, Knowledge, and Management,* 2(1), 135-148.

Olszak, C. M. and Ziemba, E. (2012) 'Critical success factors for implementing business intelligence systems in small and medium enterprises on the example of upper Silesia, Poland', *Interdisciplinary Journal of Information, Knowledge, and Management,* 7(12), 129-150.

Ong, C.-S. and Lai, J.-Y. (2007) 'Measuring user satisfaction with knowledge management systems: scale development, purification, and initial test', *Computers in human behavior,* 23(3), 1329-1346.

Oosterlaken, I. (2012) 'The capability approach, technology and design: Taking stock and looking ahead' in *The capability approach, technology and design*, Springer, 3-26.

Orr, K. (1998) 'Data quality and systems theory', *Communications of the ACM,* 41(2), 66-71.

Ouf, S. and Nasr, M. (2011) 'The cloud computing: the future of BI in the cloud', *International Journal of Computer Theory and Engineering,* 3(6), 750.

Owusu, A., Agbemabiasie, G. C., Abdurrahaman, D. T. and Soladoye, B. A. (2017) 'Determinants of business intelligence systems adoption in developing countries: An empirical analysis from Ghanaian Banks', *The Journal of Internet Banking and Commerce*, 1-25.

Oxford Business Group (2018) *The Report: Jordan 2018*, London: Oxford Business Group.

Özdemir, S. (2017) 'Teacher views on barriers to the integration of information and communication technologies (ict) in Turkish teaching'.

Ozdemir, V. E. and Hewett, K. (2010) 'The effect of collectivism on the importance of relationship quality and service quality for behavioral intentions: A cross-national and cross-contextual analysis', *Journal of international marketing,* 18(1), 41-62.

Pagoropoulos, A., Pigosso, D. C. and McAloone, T. C. (2017) 'The emergent role of digital technologies in the Circular Economy: A review', *Procedia CIRP,* 64, 19-24.

Parnell, T., Whiteford, G. and Wilding, C. (2019) 'Differentiating occupational decision-making and occupational choice', *Journal of Occupational Science,* 26(3), 442-448.

Pearson, A., Tadisina, S. and Griffin, C. (2012) 'The role of e-service quality and information quality in creating perceived value: antecedents to web site loyalty', *Information Systems Management,* 29(3), 201-215.

Peña-López, I. (2009) 'Creating effective teaching and learning environments: First results from TALIS'.

Petter, S., DeLone, W. and McLean, E. (2008) 'Measuring information systems success: models, dimensions, measures, and interrelationships', *European Journal of Information Systems,* 17(3), 236-263.

Petter, S., DeLone, W. and McLean, E. R. (2013) 'Information systems success: The quest for the independent variables', *Journal of management information systems,* 29(4), 7-62.

Petter, S. and McLean, E. R. (2009) 'A meta-analytic assessment of the DeLone and McLean IS success model: An examination of IS success at the individual level', *Information and Management,* 46(3), 159-166.

Pham, Q. T., Mai, T. K., Misra, S., Crawford, B. and Soto, R. (2016) *Critical success factors for implementing business intelligence system: Empirical study in vietnam,* translated by Springer, 567-584.

Phillimore, J. and Goodson, L. (2004) 'Progress in qualitative research in tourism: Epistemology, ontology and methodology' in *Qualitative research in tourism*, Routledge, 21-23.

Pickard, A. J. (2013) *Research methods in information,* Facet publishing.

Pitt, L. F., Watson, R. T. and Kavan, C. B. (1995) 'Service quality: a measure of information systems effectiveness', *MIS quarterly*, 173-187.

Plano Clark, V. L. and Creswell, J. W. (2009) *The mixed methods reader,* Thousand Oaks: Sage.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y. and Podsakoff, N. P. (2003) 'Common method biases in behavioral research: a critical review of the literature and recommended remedies', *Journal of Applied Psychology,* 88(5), 879.

Podsakoff, P. M., MacKenzie, S. B. and Podsakoff, N. P. (2012) 'Sources of method bias in social science research and recommendations on how to control it', *Annual review of psychology,* 63, 539-569.

Popovič, A., Hackney, R., Coelho, P. S. and Jaklič, J. (2012) 'Towards business intelligence systems success: Effects of maturity and culture on analytical decision making', *Decision support systems,* 54(1), 729-739.

Power, D. J. (2007) 'A brief history of decision support systems', *DSSResources. COM, World Wide Web, http://DSSResources. COM/history/dsshistory. html, version,* 4.

Preacher, K. J. (2015) 'Advances in mediation analysis: A survey and synthesis of new developments', *Annual review of psychology,* 66, 825-852.

Priem, R. L., Rasheed, A. M. and Kotulic, A. G. (1995) 'Rationality in strategic decision processes, environmental dynamism and firm performance', *Journal of Management,* 21(5), 913-929.

Prieto, A. V. I. (2018) 'ICT sector has booming potential if universities adapt to its demands', *The Jordan Times,* May 21, 2018,

Puklavec, B., Oliveira, T. and Popovic, A. (2014) 'Unpacking business intelligence systems adoption determinants: An exploratory study of small and medium enterprises', *Economic and Business Review for Central and South-Eastern Europe,* 16(2), 185.

Puklavec, B., Oliveira, T. and Popovič, A. (2017) 'Understanding the determinants of business intelligence system adoption stages: an empirical study of SMEs', *Industrial Management and Data Systems,* (just-accepted), 00-00.

Quinlan, C., Babin, B. J., Carr, J. C., Griffin, M. and Zikmund, W. G. (2018) *Business research methods*.

Raghunathan, S. (1999) 'Impact of information quality and decision-maker quality on decision quality: a theoretical model and simulation analysis', *Decision support systems,* 26(4), 275-286.

Raghunathan, T. S. (1992) 'Impact ofthe CEO's Participation on Information Systems Steering Committees', *Journal of management information systems,* 8(4), 83-96.

Rai, A., Lang, S. S. and Welker, R. B. (2002) 'Assessing the validity of IS success models: An empirical test and theoretical analysis', *Information Systems Research,* 13(1), 50-69.

Rai, L. (2006) 'Owning (up to) reflective writing in social work education', *Social work education,* 25(8), 785-797.

Ranjan, J. (2008) 'Hurdles and opportunities for Indian firms adopting business intelligence', *Journal of Advances in Management Research*.

Ranjan, J. (2009) 'Business intelligence: Concepts, components, techniques and benefits', *Journal of Theoretical and Applied Information Technology,* 9(1), 60-70.

Ravichandran, T. and Rai, A. (1999) 'Total Quality Management in Information Systems Development: Key Constructs and Relationships', *Journal of management information systems,* 16(3), 119-155.

Realsoft (2018) 'Business Intelligence and Data Warehousing', [online], available: http://www.realsoft-me.com/index.php/en/solutions/bi-dw [Accessed May, 23 2019].

Reich, B. H. and Benbasat, I. (2000) 'Factors that influence the social dimension of alignment between business and information technology objectives', *MIS quarterly*, 81-113.

Rezaie, S., Mirabedini, S. J. and Abtahi, A. (2017) 'Identifying key effective factors on the implementation process of business intelligence in the banking industry of Iran', *Journal of Intelligence Studies in Business,* 7(3).

Rogers, D. J. and Tanimoto, T. T. (1960) 'A computer program for classifying plants', *Science,* 132(3434), 1115-1118.

Roots, E. (2007) 'Making connections: The relationship between epistemology and research methods', *Australian Community Psychologist,* 19(1).

Rosenkranz, C., Holten, R., Räkers, M. and Behrmann, W. (2017) 'Supporting the design of data integration requirements during the development of data warehouses: a communication theory-based approach', *European Journal of Information Systems,* 26(1), 84-115.

Ross, M., Shaffer, H., Cohen, A., Freudberg, R. and Manley, H. (1974) 'Average magnitude difference function pitch extractor', *IEEE Transactions on Acoustics, Speech, and Signal Processing,* 22(5), 353-362.

Rouhani, S., Ashrafi, A., Ravasan, A. Z. and Afshari, S. (2018) 'Business intelligence systems adoption model: an empirical investigation', *Journal of Organizational and End User Computing (JOEUC),* 30(2), 43-70.

Rouhani, S., Ghazanfari, M. and Jafari, M. (2012) 'Evaluation model of business intelligence for enterprise systems using fuzzy TOPSIS', *Expert Systems with Applications,* 39(3), 3764-3771.

Sabherwal, R., Jeyaraj, A. and Chowa, C. (2006) 'Information system success: Individual and organizational determinants', *Management science,* 52(12), 1849-1864.

Salmasi, M. K., Talebpour, A. and Homayounvala, E. (2016) 'Identification and classification of organizational level competencies for BI success', *Journal of Intelligence Studies in Business,* 6(2).

Sangar, A. B. and Iahad, N. B. A. (2013) 'Critical factors that affect the success of business intelligence systems (BIS) implementation in an organization', *International Journal of Scientific and Technology Research,* 2(2), 176-180.

Satorra, A. and Saris, W. E. (1985) 'Power of the likelihood ratio test in covariance structure analysis', *Psychometrika,* 50(1), 83-90.

Saunders, G. and Courtney, J. (1985) 'A field study of the organizational factors influencing DDS success', *MIS quarterly,* 9(1), 77-88.

Saunders, M. N. K., Lewis, P. and Thornhill, A. (2019) *Research methods for business students*.

Schieder, C. and Gluchowski, P. (2011) *Towards a consolidated research model for understanding business intelligence success,* translated by.

Schmidt, M. E., Marks, J. L. and Derrico, L. (2004) 'What a difference mentoring makes: Service learning and engagement for college students', *Mentoring and Tutoring: Partnership in Learning,* 12(2), 205-217.

Schmitt, N. and Kuljanin, G. (2008) 'Measurement invariance: Review of practice and implications', *Human resource management review,* 18(4), 210-222.

Schwartz, P. M. (2016) *The factors of failure in the implementation of dashboards as a tool to measure KPI: An exploratory qualitative inquiry*, unpublished thesis Capella University.

Scott, N. (2013) 'The 3 ages of Business Intelligence: Gathering, analysing and putting it to work',

Seddon, P. and Kiew, M.-Y. (1996) 'A partial test and development of DeLone and McLean's model of IS success', *Australasian Journal of Information Systems,* 4(1), 90-109.

Seddon, P. and Yip, S.-K. (1992) 'An empirical evaluation of user information satisfaction (UIS) measures for use with general', *Journal of Information Systems,* 6(1), 75-92.

Seddon, P. B. (1997) 'A respecification and extension of the DeLone and McLean model of IS success', *Information Systems Research,* 8(3), 240-253.

Seethamraju, R. (2015) 'Adoption of software as a service (SaaS) enterprise resource planning (ERP) systems in small and medium sized enterprises (SMEs)', *Information systems frontiers,* 17(3), 475-492.

Segars, A. H. and Grover, V. (1993) 'Re-examining perceived ease of use and usefulness: A confirmatory factor analysis', *MIS quarterly*, 517-525.

Sekaran, U. and Bougie, R. (2016) *Research methods for business: A skill building approach,* 7th ed., Chichester: John Wiley and Sons.

Setia, P., Setia, P., Venkatesh, V. and Joglekar, S. (2013) 'Leveraging digital technologies: How information quality leads to localized capabilities and customer service performance', *MIS quarterly*, 565-590.

Sharda, R., Delen, D. and Turban, E. (2018) *Business intelligence, analytics, and data science: a managerial perspective,* 4th ed., New Jersey: Pearson.

Sherman, R. (2014) *Business intelligence guidebook: From data integration to analytics,* Newnes.

Shin, B. (2003) 'An exploratory investigation of system success factors in data warehousing', *Journal of the Association for Information Systems,* 4(1), 6.

Siemsen, E., Roth, A. and Oliveira, P. (2010) 'Common method bias in regression models with linear, quadratic, and interaction effects', *Organizational research methods,* 13(3), 456-476.

Simmers, C. A. and Anandarajan, M. (2001) 'User satisfaction in the Internet-anchored workplace: An exploratory study', *JITTA: Journal of Information Technology Theory and Application,* 3(5), 39.

Soliman, K. S., Mao, E. and Frolick, M. N. (2000) 'Measuring user satisfaction with data warehouses: an exploratory study', *Information and Management,* 37(3), 103-110.

Song, H.-L. (2010) *Customer adoption of Internet banking: An integration of TAM with trust, perceived risk, and quality,* translated by IEEE, 264-268.

Speier, C., Valacich, J. S. and Vessey, I. (1999) 'The influence of task interruption on individual decision making: An information overload perspective', *Decision Sciences,* 30(2), 337-360.

Spetzler, C., Winter, H. and Meyer, J. (2016) *Decision quality: Value creation from better business decisions,* Wiley Online Library.

Stafford, T. F., Turan, A. H. and Khasawneh, A. M. (2006) 'Middle-East. Com: diffusion of the internet and online shopping in Jordan and Turkey', *Journal of Global Information Technology Management,* 9(3), 43-61.

Stair, R. and Reynolds, G. (2018) *Principles of information systems,* 13th ed.*,* Boston: Cengage Learning.

Staples, L., Barker, W., Witt, K. and Oliver, D. (2002) 'Extending office telephony and network data services to a remote client through the internet',

Sugumaran, V., Sangaiah, A. K. and Thangavelu, A. (2017) *Computational intelligence applications in business intelligence and big data analytics,* CRC Press.

Symons, V. J. (1991) 'A review of information systems evaluation: content, context and process', *European Journal of Information Systems,* 1(3), 205-212.

Szajna, B. (1996) 'Empirical evaluation of the revised technology acceptance model', *Management science,* 42(1), 85-92.

Tabachnick, B. G. and Fidell, L. S. (2019) *Using multivariate statistics,* 7th ed.*,* Bostn: Pearson.

Taib, M. (2017) 'The mineral industry of Jordan', *Minerals Yearbook, 2013, Area Reports, International: Africa and the Middle East,* 3, 47.

Tamer, C., Kiley, M., Ashrafi, N. and Kuilbar, J. (2013) *Risk and benefits of business intelligence in the cloud,* translated by 86-95.

Taylor, S. and Todd, P. (1995) 'Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions', *International journal of research in marketing,* 12(2), 137-155.

Teo, T. S. H., Srivastava, S. C. and Jiang, L. (2008) 'Trust and Electronic Government Success: An Empirical Study', *Journal of management information systems,* 25(3), 99-131.

Thamir, A. and Poulis, E. (2015) 'Business intelligence capabilities and implementation strategies', *International Journal of Global Business,* 8(1), 34.

The Global Innovation Index (2018) *Global Innovation Index 2018: Energizing the World with Innovation*, Ithaca, Fontainebleau, and Geneva.

The World Bank (2018) *Global Economic Prospects*, Washington, DC: International Bank for Reconstruction and Development / The World Bank.

Tolliver, E. M. (1971) 'Myths of automated management systems', *Journal of Systems Management,* 22(3), 29-32.

Tracy, S. J. (2019) *Qualitative research methods: Collecting evidence, crafting analysis, communicating impact,* John Wiley and Sons.

Turban, E., Sharda, R. and Delen, D. (2014) *Decision support and business intelligence systems,* Pearson Education Limited.

Turpin, S. and Marais, M. A. (2004) 'Decision-making: Theory and practice', *orion,* 20(2), 143-160.

Tussyadiah, I. P., Zach, F. J. and Wang, J. (2017) 'Attitudes toward autonomous on demand mobility system: The case of self-driving taxi' in *Information and communication technologies in tourism 2017*, Springer, 755-766.

Urbach, N. and Müller, B. (2012) 'The updated DeLone and McLean model of information systems success' in *Information systems theory*, Springer, 1-18.

Urbach, N., Smolnik, S. and Riempp, G. (2009) 'The state of research on information systems success', *Business and Information Systems Engineering,* 1(4), 315-325.

Urbach, N., Smolnik, S. and Riempp, G. (2010) 'An empirical investigation of employee portal success', *The Journal of Strategic Information Systems,* 19(3), 184-206.

Urdan, T. C. (2016) *Statistics in plain English,* 4th ed.*,* London: Routledge.

Usher, R. (2002) 'A critique of the neglected epistemological assumptions of educational research' in *Understanding educational research*, Routledge, 17-40.

Vakola, M. and Nikolaou, I. (2005) 'Attitudes towards organizational change', *Employee relations*.

Van den Berg, G. J. (2001) 'Duration models: specification, identification and multiple durations' in *Handbook of econometrics*, Elsevier, 3381-3460.

Vance, A., Elie-Dit-Cosaque, C. and Straub, D. W. (2008) 'Examining trust in information technology artifacts: the effects of system quality and culture', *Journal of management information systems,* 24(4), 73-100.

Vandenberg, R. J. and Lance, C. E. (2000) 'A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research', *Organizational research methods,* 3(1), 4-70.

Vandenbosch, B. and Higgins, C. (1995) 'Executive support systems and executive preferences: a comparison of information channel selection theories', *Information Systems Journal,* 5(2), 105-118.

Venkatesh, V. and Bala, H. (2008) 'Technology acceptance model 3 and a research agenda on interventions', *Decision Sciences,* 39(2), 273-315.

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

Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. (2003) 'User Acceptance of Information Technology: Toward a Unified View', *MIS quarterly,* 27(3), 425-478.

Venkatesh, V., Thong, J. Y. and Xu, X. (2016) 'Unified theory of acceptance and use of technology: A synthesis and the road ahead', *Journal of the Association for Information Systems,* 17(5), 328-376.

Venkatesh, V., Zhang, X. and Sykes, T. A. (2011) 'Doctors Do Too Little Technology": A Longitudinal Field Study of an Electronic Healthcare System Implementation', *Information Systems Research,* 22(3), 523–546.

Vessey, I. (1991) 'Cognitive fit: A theory-based analysis of the graphs versus tables literature', *Decision Sciences,* 22(2), 219-240.

Visinescu, L. L., Jones, M. C. and Sidorova, A. (2017) 'Improving Decision Quality: The Role of Business Intelligence', *Journal of Computer Information Systems,* 57(1), 58-66.

Vitt, E., Misner, S. and Luckevich, M. (2002) *Business intelligence: Making better decisions faster,* Microsoft Press.

Vroom, V. H. (2003) 'Educating managers for decision making and leadership', *Management decision*.

Wallace, P. (2015) *Introduction to information systems,* 2nd ed., New Jersey: Pearson Higher Ed.

Walsham, G. (2017) 'ICT4D research: reflections on history and future agenda', *Information Technology for Development,* 23(1), 18-41.

Walsham, G. and Sahay, S. (2006) 'Research on information systems in developing countries: Current landscape and future prospects', *Information Technology for Development,* 12(1), 7-24.

Wang, E. T. G., Klein, G. and Jiang, J. J. (2006) 'ERP Misfit: Country of Origin and Organizational Factors', *Journal of management information systems,* 23(1), 263-292.

Wang, R. Y. and Strong, D. M. (1996) 'Beyond accuracy: What data quality means to data consumers', *Journal of management information systems,* 12(4), 5-33.

Wang, Y. D. and Emurian, H. H. (2005) 'Trust in e-commerce: consideration of interface design factors', *Journal of Electronic Commerce in Organizations (JECO),* 3(4), 42-60.

Watson, H. and Wixom, B. (2007) 'Enterprise agility and mature BI capabilities', *Business Intelligence Journal,* 12(3), 4.

Watson, H. J. (2009) 'Tutorial: Business intelligence-Past, present, and future', *Communications of the association for information systems,* 25(1), 39.

Watson, H. J., Goodhue, D. L. and Wixom, B. H. (2002) 'The benefits of data warehousing: why some organizations realize exceptional payoffs', *Information and Management,* 39(6), 491-502.

Watson, R. T., Pitt, L. F. and Kavan, C. B. (1998) 'Measuring information systems service quality: lessons from two longitudinal case studies', *MIS quarterly*, 61-79.

Watson, W. J., Baker, W. E., Bruckert, W. F., Bunton, W. P., Garcia, D. J., Horst, R. W., Iswandhi, G. I., Kinkade, D. J. and Sonnier, D. P. (1997) 'Method for verifying responses to messages using a barrier message',

Weill, P., Subramani, M. and Broadbent, M. (2002) 'IT infrastructure for strategic agility'.

Wieder, B. and Ossimitz, M.-L. (2015) 'The impact of Business Intelligence on the quality of decision making–a mediation model', *Procedia Computer Science,* 64, 1163-1171.

Williams, L. J., Vandenberg, R. J. and Edwards, J. R. (2009) '12 structural equation modeling in management research: A guide for improved analysis', *Academy of Management Annals,* 3(1), 543-604.

Williams, S. and Williams, N. (2007) *The profit impact of business intelligence,* 1st ed.*,* San Francisco: Morgan Kaufmann.

Wilson, M. and Howcroft, D. (2002) 'Re-conceptualising failure: social shaping meets IS research', *European Journal of Information Systems,* 11(4), 236-250.

Wixom, B. and Watson, H. (2012) 'The BI-based organization', *Organizational Applications of Business Intelligence Management: Emerging Trends, IGI Global, Hershey*, 193-208.

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

Wixom, B. H. and Watson, H. J. (2001) 'An empirical investigation of the factors affecting data warehousing success', *MIS quarterly*, 17-41.

Woodside, J. (2011) *Business Intelligence Best Practices for Success,* translated by Academic Conferences International Limited, 556.

World Economic Forum (2019) *The Global Competitiveness Report 2019*, World Economic Forum.

World Trade Organization (2016) *Annual report 2016*, Geneva: World Trade Organization.

Xin, M. and Choudhary, V. (2019) 'IT Investment under competition: The role of implementation failure', *Management science,* 65(4), 1909-1925.

Xu, H. and Hwang, M. I. (2007) 'The effect of implementation factors on data warehousing success: An exploratory study', *Journal of Information, Information Technology, and Organizations,* 2, 1.

Yamane, T. (1967) *Statistics : an introductory analysis - 2nd ed,* New York: Harper and Row.

Yeoh, W., Gao, J. and Koronios, A. (2008) 'Towards a critical success factor framework for implementing business intelligence systems: A Delphi study in engineering asset management organizations' in *Research and Practical Issues of Enterprise Information Systems II*, Springer, 1353-1367.

Yeoh, W. and Koronios, A. (2010) 'Critical success factors for business intelligence systems', *Journal of Computer Information Systems,* 50(3), 23-32.

Yeoh, W. and Popovič, A. (2016) 'Extending the understanding of critical success factors for implementing business intelligence systems', *Journal of the Association for Information Science and Technology,* 67(1), 134-147.

Yogev, N., Fink, L. and Even, A. (2012) *How Business Intelligence Creates Value,* translated by 84.

Zhang, X. and Prybutok, V. R. (2005) 'A consumer perspective of e-service quality', *IEEE transactions on Engineering Management,* 52(4), 461-477.

Appendix 1: The most common implementation factors cited in the reviewed literature

		Implementation factors									
Authors	**Country/Region**	**Management support**	**Data source systems**	**Resources**	**Business plan and vision**	**IT infrastructure**	**Champion**	**Team skills**	**User participation**	**Project management**	**Change management**
Wixom and Watson, 2001	USA	1	1	1		1	1	1	1		
Xu and Hwang, 2007	USA	1	1		1	1		1	1	1	
Yeoh et al., 2008	Australia	1	1		1	1	1			1	
Arnott, 2008	Australia	1		1	1	1	1	1		1	
Hwang and Xu, 2008	USA	1	1	1	1	1		1	1	1	
Yeoh and Koronios, 2010	Australia		1		1	1	1	1		1	1
Hawking and Sellitto, 2010		1	1	1		1		1	1		1
Woodside, 2011	USA	1		1					1	1	
Hasan et al., 2012	Iran	1	1			1			1		
Olszak and Ziemba, 2012	Poland	1	1	1	1	1		1		1	1
Işık et al., 2013	USA		1		1						
Dawson and Van Belle, 2013	South Africa	1	1	1		1	1		1		
Anjariny and Zeki, 2013	Malaysia	1						1	1	1	
Puklavec et al., 2014	European Union	1	1	1			1				
Boonsiritomachai et al., 2014	Thailand			1							
Boyton et al., 2015		1			1						1
Grublješič and Jaklič, 2015		1	1	1					1	1	1
Nasab et al., 2015	Malaysia	1	1	1	1		1	1	1		
Yeoh and Popovič, 2016	Australia	1	1		1	1	1				1
Mesaros et al., 2016	Slovak	1	1		1			1	1	1	
Acheampong and Moyaid, 2016	developing country	1									
Pham et al., 2016	Vietnam	1	1		1	1	1				1
Hung et al., 2016		1						1			
Audzeyeva and Hudson, 2016	UK	1									
Salmasi et al., 2016	Iran			1		1					
García and Pinzón, 2017	Colombia	1	1	1	1		1	1			1
Hatta et al., 2017	Malaysia			1							
Owusu et al., 2017	Ghana	1		1			1				
Rezaie et al., 2017	Iran	1	1	1	1	1	1	1	1	1	1
Lautenbach et al., 2017	South Africa	1									
Puklavec et al., 2017	European Union	1	1	1			1				
	Total	**26**	**19**	**16**	**14**	**14**	**13**	**13**	**12**	**11**	**9**

Appendix 2: Translator's affidavit and the translated questionnaire.

ABUGHAZALEH TRANSLATION & COMMERCIAL SERVICES — AGATO TRANSLATION — ابو غزالة للترجمة والخدمات التجارية

Sunday, 12th of August, 2018 AD

" *Translator's Affidavit* "

I, the undersigned / AHMAD MOHAMMAD AHMAD SAMARA; the General Manager of ABU-GHAZALEH AUTHORIZED TRANSLATION OFFICE, hereby certify that we are an Experienced, Competent & Authorized True and Faithful Translation Office of both English & Arabic Languages.

Having read the above, I hereby sign and stamp with my official Seal.

Translator's Signature

....

ابو غزالة للترجمة والخدمات التجارية AGATo 06/4622310 & Commercial Services Abu Ghazaleh Translation

عزيزي المتجاوب،

يقوم الباحث حالياً بدراسة استقصائية تهدف إلى تقييم العوامل المرتبطة بتطبيق ذكاء الأعمال وتأثيراتها على جودة القرار في قطاع التعدين الأردني. سيساهم هذا البحث في تحديد معوقات التنفيذ الفعال لذكاء الأعمال في أداء شركتك، وبالتالي يمكن معالجتها بسهولة.

أود أن أؤكد أنه سيتم تحليل إجاباتك بشكل جماعي واستخدامها فقط لأغراض البحث الأكاديمي. لن يتم الكشف عن إجاباتك وسيتم حفظها في مكان آمن في الجامعة.

بعد تحليل الاستبيانات، يحرص الباحث على تزويد صانع القرار في شركتك بنتائج الدراسة وآمل أن تكون مفيدة. لذلك، أود دعوتك للمشاركة بتعبئة هذا الاستبيان والذي لن يستغرق أكثر من ١٥ دقيقة.

إذا كنت بحاجة إلى مزيد من المعلومات فيرجى عدم التردد من الاتصال بي.

مع خالص تحياتي،

عزيزي / عزيزتي

أنت مدعو للمشاركة في الدراسة البحثية المذكورة أعلاه. وقبل أن تقرر المشاركة، من المهم أن تفهم سبب إجراء البحث وما ينطوي عليه. يرجى أخذ الوقت لقراءة المعلومات التالية. إذا كان هناك أي شيء غير واضح أو إذا كنت ترغب في مزيد من المعلومات فالرجاء عدم التردد في الاتصال بالمشرف أو بي. تفاصيل الاتصال الخاصة بنا موجودة في نهاية هذا النموذج. مشاركتك في هذه الدراسة طوعية بالكامل. قد تستغرق بعض الوقت لتقرر المشاركة أو عدم المشاركة. لست بحاجة للإجابة على جميع الأسئلة.

اسم المشروع: تنفيذ ذكاء الأعمال: تقييم لتأثيره على جودة صنع القرار في قطاع التعدين في الأردن

الهدف من هذه الدراسة هو تعزيز المعرفة والفهم لتنفيذ ذكاء الأعمال والعوامل التي تؤثر على هذا التنفيذ وكيف يؤثر ذكاء الأعمال على جودة صنع القرار في قطاع التعدين الأردني.

مشاركتك في هذه الدراسة طوعية بالكامل، لذا يعود لك قرار ما إذا كنت ستشارك فيها أم لا. إذا كنت ترغب في المشاركة ستحصل على ورقة المعلومات هذه. لا تزال لديك حرية الانسحاب في أي وقت ودون إبداء الأسباب. يمكنك سحب مشاركتك في أي وقت خلال الدراسة دون التأثير على حقوقك. **(يرجى ملاحظة أنك لن تكون قادراً على سحب بياناتك بمجرد إرسالها)** لأن البيانات مجهولة الهوية عند جمعها.

تتم مشاركتك في الدراسة عن طريق الاشتراك في الاستبيان الذي سيكون بمثابة المصدر الرئيسي للبيانات. سيأخذ الاستبيان حوالي **١٠ إلى ١٥ دقيقة**. وسوف يركز كامل الاستبيان على الدراسة.

ستكون البيانات التي يتم جمعها للأغراض البحثية والأكاديمية فقط وستظل هويتك سرية أو "مجهولة الهوية". لن يطلب منك كتابة اسمك في الاستبيان، وأؤكد أنه لن تكون هناك مخاطر عليك بسبب مشاركتك. سيتم تخزين البيانات على كلمة مرور الجامعة المحمية.

ستستخدم البيانات الديموغرافية مثل العمر والجنس والرتبة والخبرة لغرض البحث الأكاديمي فقط. سيتم الحفاظ على سرية بياناتك الشخصية ولن تستخدم لتحديد هوية أي فرد. ستخزن البيانات التي يتم جمعها على أجهزة كمبيوتر محمية بكلمة مرور في جامعة جون مورس ليفربول في المملكة المتحدة. يتم إعطاء الوصول إلى أجهزة الكمبيوتر هذه للباحث فقط. سيتم تخزين البيانات لغرض هذه الدراسة لسنوات الخمسة القادمة فقط وسيتم إتلافها بعد ذلك.

وافقت لجنة أخلاقيات البحوث الجامعية على هذه الدراسة بالإشارة:
نشكرك على مساعدتك القيمة، ونقدر تعاونك عالياً.

الجزء (ب): معلومات عامة

١. ما هو جنسك؟
٢. يرجى ذكر فئتك العمرية (بالسنوات)
٣. ما هو أعلى مستوى تعليمي أكملته؟
٤. يرجى ذكر اسم شركتك.
٥. ما هو مستواك الإداري في المؤسسة؟
٦. ما هو مجالك الوظيفي؟
٧. يوجد لدى مؤسستك نظام ذكاء أعمال؟

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٨. ما هي تقنية أو برامج ذكاء الأعمال المستخدمة في مؤسستك؟
٩. أنا أعتبر نفسي:
١٠. كم مرة تستخدم نظام ذكاء الأعمال؟
١١. منذ متى يستخدم نظام ذكاء الأعمال في مؤسستك؟

على مقياس يتراوح ما بين لا أوافق بشدة (١) أوافق بشدة (٥)، يرجى ذكر مدى موافقتك / عدم موافقتك على العبارات التالية:

الجزء (ج-١): خطة العمل والرؤية "خطة العمل والرؤية هي خطة المشروع لتنفيذ ذكاء الأعمال".

١. تتماشى خطة العمل والرؤية مع رسالة الشركة وغاياتها وأهدافها واستراتيجياتها.
٢. توفر خطة العمل والرؤية أهدافاً محددة بوضوح.
٣. تحتوي خطة العمل والرؤية على أهداف واقعية.
٤. توفر خطة العمل والرؤية فوائد وتخصيص موارد وتكاليف ومخاطر وجدول زمني.
٥. توفر خطة العمل والرؤية رؤية طويلة الأجل تتكامل مع مبادرات الشركة.

الجزء (ج-٢): دعم الإدارة.

٦. عموماً، شجعت الإدارة على استخدام ذكاء الأعمال
٧. كان رضا المستخدمين شاغلاً رئيسياً للإدارة
٨. تلتزم الإدارة بشدة بالتنفيذ الناجح لذكاء الأعمال
٩. تولي الإدارة اهتماماً فعالاً لمشاكل ونجاحات ذكاء الأعمال.
١٠. توفر الإدارة الموارد اللازمة لتنفيذ ذكاء الأعمال.

الجزء (ج-٣): البطل: شخص داخل المنظمة يدعم ويطور المشروع بنشاط.

١١. يتواصل بطل المشروع مع فريق ومستخدمي المشروع
١٢. يزود بطل المشروع المعلومات ذات الصلة مع فريق ومستخدمي المشروع.
١٣. يتمتع بطل المشروع بقيادة قوية
١٤. بطل المشروع مخول باتخاذ القرارات.
١٥. يتمتع بطل المشروع بالكفاءة المهنية والفنية.

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الجزء (ج-٤): الموارد.

١٦. تم تمويل نظام ذكاء الأعمال بشكل ملائم.

١٧. كان لدى نظام ذكاء الأعمال عدد كافٍ من أعضاء الفريق لإنجاز العمل.

١٨. أعطي نظام ذكاء الأعمال وقتاً كافياً لإكماله.

الجزء (ج – ٥): إدارة المشروع

١٩. تم تحديد المهام ونطاق المشروع بشكل جيد خلال تنفيذ ذكاء الأعمال

٢٠. تم خلال تنفيذ ذكاء الأعمال تحديد معالم مقابل نتائج قابلة للقياس.

٢١. كان هناك التزام بتعزيز وإدارة تنفيذ مشروع تنفيذ ذكاء الأعمال.

٢٢. تم توفير إيصال منتظم للتوقعات والتحديات والتعليم والتدريب والدعم خلال تنفيذ ذكاء الأعمال.

الجزء (ج-٦): مهارات الفريق

٢٣. كان أعضاء فريق المشروع من مجالات خبرة مختلفة.

٢٤. كان أعضاء فريق المشروع (بما فيهم الاستشاريين) يتمتعون بالمهارات الفنية المناسبة لذكاء الأعمال.

٢٥. كان أعضاء فريق المشروع يتمتعون بمهارات جيدة في التعامل مع الآخرين.

٢٦. كان أعضاء فريق المشروع يتمتعون بمهارات مكملة لبعضها البعض.

٢٧. كان أعضاء فريق المشروع يتمتعون بمجموعة متنوعة من التجارب المختلفة.

٢٨. كان أعضاء فريق المشروع من خلفيات وظيفية مختلفة.

الجزء (ج-٧): إدارة التغيير

٢٩. يتم تشجيع الموظفين أو مكافأتهم من رؤسائهم للتعبير عن وتبادل وجهات نظرهم وأفكارهم بشأن العمل.

٣٠. توجد رغبة للتعاون بين الوحدات التنظيمية.

٣١. تتوفر موارد تنظيمية كافية للموظفين (مثل تدريب وتعليم كافيين للمستخدمين).

الجزء (ج-٨): نظام مصدر البيانات

٣٢. نُفذت تعاريف مشتركة لبنود البيانات الرئيسية في نظام المصدر

٣٣. كانت مصادر البيانات المستخدمة لذكاء الأعمال تطبيقات / أنظمة متنوعة ومتباينة

٣٤. يجب تعديل عدد كبير من أنظمة المصدر لتوفير بيانات لذكاء الأعمال.

الجزء (ج-٩): البنية التحتية لتكنولوجيا المعلومات

٣٥. كان يوجد بنية تحتية مناسبة للأجهزة والبرمجيات والشبكات قبل تنفيذ ذكاء الأعمال

٣٦. تم تنفيذ تقنيات الخوادم وقاعدة البيانات الضرورية قبل تنفيذ نظام ذكاء الأعمال

٣٧. تم تركيب الأجهزة والبرمجيات اللازمة قبل بدء هذا المشروع

الجزء (ج-١٠): المواقف من التكنولوجيا

٣٨. يعد استخدام نظام ذكاء الأعمال فكرة جيدة

٣٩. نظام ذكاء الأعمال يجعل العمل أكثر إثارة متعةً

٤٠. العمل بنظام ذكاء الأعمال ممتع

٤١. أحب العمل بنظام ذكاء الأعمال

الجزء (ج-١١): الثقة

٤٢. يمكنني الوثوق بنظام ذكاء الأعمال

٤٣. أثق بالمعلومات المقدمة على نظام ذكاء الأعمال

٤٤. أثق بعملية المعاملة على نظام ذكاء الأعمال

الجزء (ج-١٢): مشاركة المستخدم

٤٥. يشارك المستخدمون بنشاط في تحديد متطلبات النظام.

٤٦. يشارك المستخدمون بنشاط في تحديد احتياجات المدخلات والمخرجات.

٤٧. يشارك المستخدمون بنشاط في تطوير خطط الاختبار.

الجزء (د-١): جودة النظام

٤٨. من السهل معرفة ما إذا كان النظام يعمل بشكل صحيح أم لا.

٤٩. يستطيع نظام ذكاء الأعمال التعافي من الأخطاء والحوادث والتدخلات مع الحفاظ على أمن وسلامة البيانات

٥٠. من الممكن بسهولة تعديل نظام ذكاء الأعمال لتلبية متطلبات المستخدم المتغيرة.

٥١. يمكن بسهولة تكييف نظام ذكاء الأعمال مع بيئة تقنية أو تنظيمية جديدة.

٥٢. من السهل صيانة نظام ذكاء الأعمال.

٥٣. من السهل فهم نظام ذكاء الأعمال.

٥٤. من السهل استخدام نظام ذكاء الأعمال.

٥٥. يؤدي نظام ذكاء الأعمال وظائفه بسرعة.

الجزء (د-٢): جودة المعلومات

٥٦. يوفر نظام ذكاء الأعمال معلومات كافية

٥٧. من خلال نظام ذكاء الأعمال، أحصل على المعلومات التي احتاجها في الوقت المناسب

٥٨. أنا راضٍ عن دقة نظام ذكاء الأعمال

٥٩. المعلومات التي يوفرها نظام ذكاء الأعمال تلبي احتياجاتي

٦٠. المعلومات المقدمة من نظام ذكاء الأعمال في شكل مفيد

٦١. المعلومات المقدمة من نظام ذكاء الأعمال واضحة

الجزء (د-٣): جودة صنع القرار

٦٢. أنا راض عن نتائج هذا القرار

٦٣. أعتقد أنني اتخذت قراراً صائباً

٦٤. باستعادة الأحداث الماضية والتأمل فيها، أعتقد أنني اتخذت القرار الصحيح

٦٥. أسفر القرار الذي اتخذته عن النتيجة المرجوة.

Appendix 3: Covering letter and questionnaire.

Cover Letter

Please read the cover letter if you would like to proceed.

Dear Participant,

You are being invited to take part in the above research study. Before you decide to participate, it is important that you understand why the research is being done and what it involves. Please take time to read the following information. If there is anything that is not clear, or if you would like more information please feel free to contact my supervisor or me. Our contact details are provided at the end of this form. It is completely on voluntary basis to participate in this study. You may take time to decide to participate or not. You do not need to answer all of the questions.

Title of Project: Business Intelligence Implementation: An Evaluation of its Impact on the Quality of Decision-Making in Jordan's Mining Sector

The aim of this study is to advance knowledge and understanding of the implementation of BI, the factors that influence that implementation's success, and how BI impacts upon the quality of decision-making in the Jordanian mining sector. Your participation in this study is entirely voluntary so it is up to you to decide whether or not to take part in it. If you do wish to participate, click Next at the end of this page. You are still free to withdraw at any time and without giving a reason. You may withdraw your participation at any time during the study that will not affect your rights. (**Please note that you will not be able to withdraw your data once submitted**) as data is anonymised on collection.

Your participation in the study is by being involved in a questionnaire that would serve as the primary source of data. The questionnaire would last approximately **10 to 15 minutes**. And all the questionnaire would focus on the study.

The data collected will be solely for the research and academic purposes and your identity will be kept confidential or 'anonymous'. You will not be asked to write your name on the questionnaire therefore, I can confirm that there will be no risks to you due to your participation. The data collected will be stored on the password-protected computers at LJM University, Liverpool UK. The access to these computers is only given to the researcher.

University Research Ethics Committee has approved this study with reference:17/LBS/004.

Thank you for your valuable assistance and your co-operation are highly appreciated.

Nadeem Ali El-Adaileh
Liverpool John Moors University

Part (B): general information

1. What is your gender?

- Male
- Female

2. Please indicate your age group (years)

- Under than 20
- 21 - 30
- 31 - 40
- 41 - 50
- More than 50

3. What is the highest education level you have completed?

- PhD
- Master
- Bachelors
- Diploma
- High School

4. What is your managerial level in the organisation?

Top management	Middle management	Operational management
◯	◯	◯

5. What is your functional area?

- ◯ Business development
- ◯ Finance
- ◯ Human resources
- ◯ Information technology
- ◯ Legal
- ◯ Operations / Manufacturing
- ◯ Marketing
- ◯ Sales
- ◯ Supply chain

6. What business intelligence technology or software used in your organization?

- ◯ Microsoft business intelligence
- ◯ Oracle business intelligence
- ◯ IBM business intelligence
- ◯ SAP business intelligence
- ◯ Decision Support System
- ◯ Data Warehouse
- ◯ Reporting System
- ◯ Mixed and match of software
- ◯ Custom developed
- ◯ Management Information System
- ◯ Other

7. How Long have been using Business Intelligence system in your organization?

- ◯ less than 6 moths
- ◯ 6 moths 1 year
- ◯ 1 - 2 years
- ◯ 3 - 4 years
- ◯ 4 - 5 years
- ◯ More than 5 years

Part (C.1)

Part (C.1): Business Plan and Vision "Business Plan and Vision is the project plan for the business intelligence implementation."

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

1. The business plan and vision aligns with the company's mission, goals, objectives, and strategies.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
◯	◯	◯	◯	◯

2. The business plan and vision contain quantified goals and objectives.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
◯	◯	◯	◯	◯

3. The business plan and vision contain detailed action plans/strategies that support company direction.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

4. The business plan and vision activities are instrumental in providing cross-functional integration

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

5. The business plan and vision contribute to the success of the company and the business intelligence system.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (C.2)

Part (C.2): Management Support.

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

6. Overall, management has encouraged the use of business intelligence

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

7. User satisfaction has been a major concern of management

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

8. Management is strongly committed to the successful implementation of business intelligence

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

9. Management takes an active interest in a business intelligence problems and successes.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

10. Management provides necessary resources for business intelligence implementation

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (C.3)

Part (C.3): Champion: a person within the organization who actively supports and promotes the project.

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

11. The project champion willing to listen to implementation problems.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree

12. The project champion encourages people to work as a team.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree

13. The project champion primarily concerned with getting the job done.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree

14. The project champion encourages participative decision-making.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree

15. The project champion came from information system domain.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree

Part (C.4)

Part (C.4): Resources.

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

16. The Business Intelligence project was adequately funded.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree

17. The Business Intelligence project had enough team members to get the work done.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree

18. The Business Intelligence project was given enough time for completion

Strongly disagree	Disagree	Neutral	Agree	Strongly agree

Part (C.5)

Part (C.5): Project Management

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

19. Project management success to assess project performance in the early stages of implementation.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree

20. Project management success in measuring implementation performance.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

21. Project management success in gaining control of business intelligence implementation.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

22.Project management success in communicating between business intelligence implementation team members and other company members.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (C.6)

Part (C.6): Team Skills

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

23. The members of the project team were from different areas of expertise.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

24. The members of the project team (including consultants) had the right technical skills for business intelligence.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

25. The members of the project team had good interpersonal skills.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

26. The members of the project team had skills that complemented each other.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

27. The members of the project team had a variety of different experiences.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

28. The members of the project team varied in functional backgrounds.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (C.7)

Part (C.7): Change Management

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

29. The change management support was available whenever I needed it.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

30. The change management consultants understood my problems well.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

31. The change management consultants resolved the problems I faced.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (C.8)

Part (C.8): Data Source System

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

32. Common definitions for key data items were implemented across the source system

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

33. The data sources used for business intelligence were diverse and disparate applications/systems

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

34. A significant number of source systems had to be modified to provide data for business intelligence

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (C.9)

Part (C.9): Information Technology Infrastructure

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

35. Appropriate hardware, software, and network infrastructures were in place prior to business intelligence implementation

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

36. Necessary server and database technologies were implemented before implementing the business intelligence system

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

37. Necessary hardware and software were installed before the start of this project

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (C.10)

Part (C.10): Attitudes Toward Technology

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

38. Using Business intelligence system is a good idea

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

39. Business intelligence system makes work more interesting

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

40. working with Business intelligence system is fun

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

41. I like working with Business intelligence system

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (C.11)

Part (C.11): Trust

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

42. I can trust business intelligence system

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

43. I trust the information presented on business intelligence system

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

44. I trust the transaction process on business intelligence system

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (C.12)

Part (C.12): User Participation

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

45. Users actively participate in determining system requirements.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

46. Users actively participate in identifying input/output needs.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

47. Users actively participate in developing test plans.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (D.1)

Part (D.1): System Quality

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

48. Business intelligence system is reliable (it is always up and running, runs without errors, and does what it is supposed to do)

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

49. It is easy to tell whether the system is functioning correctly.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

50. Business intelligence system can recover from errors, accidents, and intrusions while maintaining data security and integrity

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

51. Business intelligence system can easily be modified to meet changing user requirements.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

52. Business intelligence system can easily be adapted to a new technical or organizational environment.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

53. Business intelligence system is easy to maintain.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

54. Business intelligence system is easy to understand.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

55. Business intelligence system is easy to use.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

56. Business intelligence system performs its functions quickly.

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (D.2)

Part (D.2): Information Quality

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

57. Business intelligence system provides sufficient information

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

58. Through business intelligence system, I get the information I need in time

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

59. I am satisfied with the accuracy of business intelligence system

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

60. Information provided by business intelligence system meets my needs

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

61. Information provided by business intelligence system is in a useful format

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

62. Information provided by business intelligence system is clear

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Part (D.3)

Part (D.3): Quality of Decision Making

On a scale ranging from strongly disagree (1) to strongly agree (5), please indicate your level of agreement/disagreement regarding the following statements:

63. As a result of business intelligence system, I am satisfied with the outcomes of this decision

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

64. As a result of business intelligence system, I believe I made good decision

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

65. As a result of the business intelligence system, in retrospect, I believe I made the right decision

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

66. As a result of business intelligence system, the decision that I made resulted in the desired outcome

Strongly disagree	Disagree	Neutral	Agree	Strongly agree
○	○	○	○	○

Appendix 4: Multicollinearity results

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	MS_AVG	.526	1.903
	CH_AVG	.565	1.769
	R_AVG	.544	1.837
	PM_AVG	.630	1.587
	TS_AVG	.653	1.531
	CHM_AVG	.781	1.281
	DSS_AVG	.641	1.561
	ITI_AVG	.698	1.433
	ATT_AVG	.638	1.567
	T_AVG	.514	1.944
	UP_AVG	.801	1.249

a. Dependent Variable: BPV_AVG

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	CH_AVG	.630	1.586
	R_AVG	.543	1.841
	PM_AVG	.642	1.557
	TS_AVG	.639	1.564
	CHM_AVG	.782	1.279
	DSS_AVG	.644	1.553
	ITI_AVG	.710	1.409
	ATT_AVG	.648	1.544
	T_AVG	.512	1.953
	UP_AVG	.798	1.254
	BPV_AVG	.732	1.366

a. Dependent Variable: MS_AVG

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	R_AVG	.552	1.811
	PM_AVG	.629	1.591
	TS_AVG	.642	1.558
	CHM_AVG	.779	1.283
	DSS_AVG	.645	1.550
	ITI_AVG	.700	1.429
	ATT_AVG	.649	1.542
	T_AVG	.513	1.950
	UP_AVG	.791	1.264
	BPV_AVG	.735	1.361
	MS_AVG	.588	1.700

a. Dependent Variable: CH_AVG

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	PM_AVG	.636	1.573
	TS_AVG	.645	1.550
	CHM_AVG	.793	1.260
	DSS_AVG	.637	1.570
	ITI_AVG	.718	1.392
	ATT_AVG	.641	1.559
	T_AVG	.527	1.896
	UP_AVG	.799	1.251
	BPV_AVG	.733	1.364
	MS_AVG	.525	1.903
	CH_AVG	.573	1.747

a. Dependent Variable: R_AVG

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	TS_AVG	.644	1.553
	CHM_AVG	.787	1.270
	DSS_AVG	.634	1.576
	ITI_AVG	.697	1.435
	ATT_AVG	.640	1.562
	T_AVG	.515	1.943
	UP_AVG	.797	1.255
	BPV_AVG	.736	1.359
	MS_AVG	.539	1.856
	CH_AVG	.565	1.770
	R_AVG	.551	1.815

a. Dependent Variable: PM_AVG

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	CHM_AVG	.778	1.286
	DSS_AVG	.638	1.567
	ITI_AVG	.709	1.411
	ATT_AVG	.638	1.568
	T_AVG	.532	1.880
	UP_AVG	.790	1.265
	BPV_AVG	.748	1.338
	MS_AVG	.525	1.903
	CH_AVG	.565	1.769
	R_AVG	.548	1.825
	PM_AVG	.631	1.584

a. Dependent Variable: TS_AVG

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	DSS_AVG	.634	1.576
	ITI_AVG	.695	1.439
	ATT_AVG	.639	1.566
	T_AVG	.529	1.890
	UP_AVG	.799	1.251
	BPV_AVG	.736	1.358
	MS_AVG	.529	1.889

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	ITI_AVG	.706	1.416
	ATT_AVG	.641	1.560
	T_AVG	.521	1.918
	UP_AVG	.790	1.266
	BPV_AVG	.739	1.353
	MS_AVG	.533	1.876
	CH_AVG	.573	1.746
	R_AVG	.545	1.834

		Tolerance	VIF
	CH_AVG	.565	1.769
	R_AVG	.555	1.801
	PM_AVG	.636	1.573
	TS_AVG	.641	1.561

a. Dependent Variable: CHM_AVG

		Tolerance	VIF
	PM_AVG	.627	1.596
	TS_AVG	.643	1.555
	CHM_AVG	.776	1.289

a. Dependent Variable: DSS_AVG

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	ATT_AVG	.641	1.560
	T_AVG	.511	1.956
	UP_AVG	.791	1.264
	BPV_AVG	.735	1.360
	MS_AVG	.537	1.863
	CH_AVG	.567	1.762
	R_AVG	.562	1.780
	PM_AVG	.629	1.591
	TS_AVG	.652	1.533
	CHM_AVG	.777	1.288
	DSS_AVG	.645	1.550

a. Dependent Variable: ITI_AVG

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF	
UP_AVG	.798	1.253	1.253
BPV_AVG	.736	1.359	1.359
MS_AVG	.526	1.901	1.901
CH_AVG	.564	1.772	1.772
R_AVG	.560	1.786	1.786
PM_AVG	.631	1.585	1.585
TS_AVG	.665	1.504	1.504
CHM_AVG	.803	1.246	1.246
DSS_AVG	.647	1.546	1.546
ITI_AVG	.694	1.440	1.440
ATT_AVG	.655	1.526	1.526

a. Dependent Variable: T_AVG

Coefficients[a]

Collinearity Statistics		Collinearity Statistics Tolerance	VIF
1	T_AVG	.525	1.904
	UP_AVG	.801	1.248
	BPV_AVG	.732	1.366
	MS_AVG	.533	1.875
	CH_AVG	.573	1.747
	R_AVG	.546	1.831
	PM_AVG	.629	1.590
	TS_AVG	.639	1.564
	CHM_AVG	.777	1.287
	DSS_AVG	.638	1.568
	ITI_AVG	.698	1.433

a. Dependent Variable: ATT_AVG

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	BPV_AVG	.742	1.348
	MS_AVG	.531	1.884
	CH_AVG	.564	1.772
	R_AVG	.550	1.819
	PM_AVG	.632	1.582
	TS_AVG	.640	1.563
	CHM_AVG	.786	1.272
	DSS_AVG	.635	1.575
	ITI_AVG	.696	1.437
	ATT_AVG	.647	1.545
	T_AVG	.517	1.934

a. Dependent Variable: UP_AVG

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality

Appendix 5: CFA 'test run' result

- **Standardized Regression Weights: (Group number 1 - Default model)**

			Estimate
BPV1	<---	BPV	.773
BPV2	<---	BPV	.899
BPV3	<---	BPV	.892
BPV4	<---	BPV	.798
BPV5	<---	BPV	.857
MS1	<---	MS	.800
MS2	<---	MS	.747
MS3	<---	MS	.806
MS4	<---	MS	.771
MS5	<---	MS	.749
CH2	<---	CH	.848
CH3	<---	CH	.841
CH4	<---	CH	.836
CH5	<---	CH	.841
CH1	<---	CH	.859
R2	<---	R	.822
R3	<---	R	.851
R1	<---	R	.832
PM2	<---	PM	.780
PM3	<---	PM	.768
PM4	<---	PM	.778
PM1	<---	PM	.796
TS2	<---	TS	.707
TS3	<---	TS	.689
TS4	<---	TS	.469
TS5	<---	TS	.738
TS6	<---	TS	.748
TS1	<---	TS	.769
CHM2	<---	CHM	.771
CMH3	<---	CHM	.828
CHM1	<---	CHM	.882
DSS2	<---	DSS	.692
DSS3	<---	DSS	.730
DSS1	<---	DSS	.768
ITI2	<---	ITI	.747
ITI3	<---	ITI	.778
ITI1	<---	ITI	.771

			Estimate
T2	<---	T	.782
T3	<---	T	.818
T1	<---	T	.800
UP2	<---	UP	.783
UP3	<---	UP	.832
UP1	<---	UP	.824
SQ9	<---	SQ	.430
SQ8	<---	SQ	.824
SQ7	<---	SQ	.896
SQ6	<---	SQ	.905
SQ5	<---	SQ	.889
SQ4	<---	SQ	.897
SQ3	<---	SQ	.897
SQ2	<---	SQ	.844
SQ1	<---	SQ	.891
IQ5	<---	IQ	.735
IQ4	<---	IQ	.755
IQ3	<---	IQ	.711
IQ2	<---	IQ	.735
IQ1	<---	IQ	.862
DQ4	<---	DQ	.834
DQ3	<---	DQ	.660
DQ2	<---	DQ	.615
DQ1	<---	DQ	.711
IQ6	<---	IQ	.714
ATT2	<---	ATT	.816
ATT3	<---	ATT	.820
ATT4	<---	ATT	.844
ATT1	<---	ATT	.777

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality

- **Squared Multiple Correlations: (Group number 1 - Default model)**

	Estimate
DQ1	.506
DQ2	.378
DQ3	.436
DQ4	.696
IQ1	.743
IQ2	.540
IQ3	.506
IQ4	.570
IQ5	.540
IQ6	.510
SQ1	.794
SQ2	.712
SQ3	.805
SQ4	.804
SQ5	.790
SQ6	.818
SQ7	.803
SQ8	.679
SQ9	.185
UP1	.678
UP3	.693
UP2	.613
T1	.641
T3	.669
T2	.612
ATT1	.604
ATT4	.713
ATT3	.672
ATT2	.666

	Estimate
DSS1	.589
DSS3	.533
DSS2	.479
CHM1	.777
CMH3	.685
CHM2	.595
TS1	.591
TS6	.559
TS5	.545
TS4	.220
TS3	.475
TS2	.499
PM1	.634
PM4	.605
PM3	.589
PM2	.608
R1	.693
R3	.724
R2	.676
CH1	.738
CH5	.707
CH4	.699
CH3	.707
CH2	.719
MS5	.561
MS4	.594
MS3	.649
MS2	.558
MS1	.639
BPV5	.734
BPV4	.638
BPV3	.795
BPV2	.809
BPV1	.597

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality

- **Modification Indices (Group number 1 - Default model)**

Covariances: (Group number 1 - Default model)

			M.I.	Par Change
e65	<-->	e66	32.614	.097
e64	<-->	SQ	4.741	.028
e64	<-->	T	4.518	.038
e64	<-->	R	4.571	-.046
e64	<-->	e65	21.634	-.083
e63	<-->	e64	9.135	.042
e61	<-->	UP	5.146	.056
e61	<-->	DSS	5.722	-.041
e61	<-->	CH	4.795	.047
e61	<-->	BPV	5.832	.048
e61	<-->	e65	5.761	.045
e60	<-->	e61	42.608	.112
e59	<-->	e62	5.209	-.028
e58	<-->	e64	6.431	.044
e58	<-->	e61	12.292	-.063
e58	<-->	e60	26.722	-.085
e58	<-->	e59	25.520	.085
e57	<-->	e61	13.380	-.065
e57	<-->	e58	14.842	.065
e56	<-->	e65	4.793	-.036
e55	<-->	e65	5.261	.041
e55	<-->	e63	4.574	-.031
e54	<-->	ITI	5.514	.037
e54	<-->	e56	7.865	-.037
e54	<-->	e55	49.158	.101
e53	<-->	e56	5.484	-.034
e53	<-->	e55	13.793	.058
e53	<-->	e54	18.981	.057
e52	<-->	e56	6.358	-.035
e52	<-->	e54	5.685	.031
e51	<-->	DSS	4.036	-.029
e51	<-->	e56	13.111	.050
e51	<-->	e55	4.411	-.032
e51	<-->	e54	30.657	-.070
e50	<-->	IQ	4.330	.031
e50	<-->	e65	6.480	-.041
e50	<-->	e64	4.697	.035
e35	<-->	e36	5.086	-.049
e34	<-->	e53	4.232	-.039

			M.I.	Par Change
e50	<-->	e56	18.311	.062
e50	<-->	e55	29.209	-.085
e50	<-->	e53	27.885	-.076
e50	<-->	e51	13.909	.051
e49	<-->	e54	4.983	-.032
e48	<-->	MS	4.666	.091
e48	<-->	BPV	4.440	.089
e48	<-->	e66	4.712	.081
e48	<-->	e61	4.872	.088
e48	<-->	e54	6.675	-.083
e47	<-->	e48	5.308	-.114
e46	<-->	e52	4.746	-.043
e44	<-->	e50	5.862	-.045
e42	<-->	e66	5.913	-.048
e41	<-->	MS	12.806	-.085
e41	<-->	e46	6.162	.069
e41	<-->	e45	8.703	-.082
e39	<-->	DSS	5.228	-.043
e39	<-->	TS	5.127	.042
e38	<-->	DSS	5.589	.048
e38	<-->	e45	7.821	.078
e38	<-->	e44	4.800	.056
e38	<-->	e43	4.651	-.054
e38	<-->	e40	5.221	.056
e38	<-->	e39	7.584	-.067
e37	<-->	ITI	4.085	.042
e37	<-->	e61	5.817	.051
e37	<-->	e48	5.397	-.104
e36	<-->	SQ	4.165	.028
e36	<-->	UP	4.028	-.052
e36	<-->	e63	5.743	-.038
e36	<-->	e48	4.572	.090
e35	<-->	e63	5.867	.042
e35	<-->	e45	8.648	.080
e35	<-->	e37	4.277	.048
e22	<-->	e35	4.139	.045
e22	<-->	e30	4.604	.052

e34	<-->	e51	4.150	-.037
e34	<-->	e48	6.799	-.119
e33	<-->	SQ	5.967	.039
e33	<-->	ITI	4.708	-.051
e33	<-->	e66	4.673	-.046
e33	<-->	e53	6.452	.051
e33	<-->	e48	4.749	.105
e32	<-->	e51	5.002	-.041
e31	<-->	ITI	5.279	.053
e31	<-->	BPV	4.762	.052
e31	<-->	e45	4.985	-.062
e30	<-->	ITI	4.316	-.052
e30	<-->	e34	5.525	-.064
e29	<-->	e50	5.555	.048
e29	<-->	e34	4.972	.060
e28	<-->	e65	6.499	-.050
e28	<-->	e42	4.657	-.048
e27	<-->	DQ	4.061	-.041
e27	<-->	e63	7.620	-.045
e27	<-->	e55	5.473	-.046
e27	<-->	e53	4.120	-.037
e27	<-->	e32	4.711	.052
e26	<-->	e56	6.609	-.045
e26	<-->	e30	4.918	.056
e25	<-->	SQ	5.245	.047
e25	<-->	CHM	5.853	-.090
e25	<-->	MS	6.221	.076
e25	<-->	BPV	6.733	-.080
e25	<-->	e48	15.580	.243
e25	<-->	e45	4.223	.074
e25	<-->	e42	6.858	.086
e24	<-->	e36	9.228	-.065
e24	<-->	e35	5.092	.053
e24	<-->	e34	4.657	.051
e24	<-->	e27	8.310	-.063
e24	<-->	e26	11.047	.071
e23	<-->	R	4.158	-.049
e23	<-->	e57	7.915	-.055
e23	<-->	e38	5.667	.059
e22	<-->	T	4.416	.039
e22	<-->	ITI	9.188	.061
e22	<-->	e57	7.160	-.049
e21	<-->	e53	4.624	.044
e21	<-->	e50	7.262	-.055
e20	<-->	DSS	4.114	-.039
e20	<-->	CHM	4.212	-.057
e20	<-->	e30	5.142	-.062
e19	<-->	ITI	5.904	-.058
e19	<-->	e48	4.050	.098
e18	<-->	MS	4.776	.054
e18	<-->	e64	8.266	-.065
e18	<-->	e60	5.638	.051
e18	<-->	e50	4.509	-.044
e18	<-->	e21	5.208	.066
e17	<-->	MS	4.521	-.052
e17	<-->	e29	4.185	-.059
e16	<-->	e46	4.558	-.059
e15	<-->	e44	6.794	.063
e15	<-->	e25	4.318	-.069
e15	<-->	e22	4.331	-.045
e15	<-->	e18	4.856	-.059
e14	<-->	e41	9.873	.081
e14	<-->	e40	8.309	-.071
e14	<-->	e25	5.619	.079
e13	<-->	PM	7.179	.065
e12	<-->	e48	5.167	-.095
e12	<-->	e43	7.722	-.060
e12	<-->	e40	5.817	.054
e12	<-->	e35	4.896	.050
e12	<-->	e15	5.173	.050
e11	<-->	ATT	8.044	.070
e11	<-->	TS	5.750	-.041
e11	<-->	e52	7.460	-.045
e11	<-->	e50	4.035	.034
e11	<-->	e48	4.616	.089
e11	<-->	e36	6.190	.051
e11	<-->	e24	4.865	-.047
e11	<-->	e15	4.282	-.045
e11	<-->	e13	4.623	.046
e10	<-->	e46	4.190	-.059
e10	<-->	e43	4.754	-.056
e10	<-->	e30	5.264	-.068
e10	<-->	e29	6.163	.072
e8	<-->	DSS	5.315	.045

			M.I.	Par Change
e8	<-->	e32	5.921	.061
e7	<-->	UP	4.276	.064
e7	<-->	e41	5.048	-.063

e7	<-->	e8	4.879	.059
e6	<-->	SQ	5.536	.036
e6	<-->	e55	4.115	.042
e6	<-->	e19	5.774	.063
e5	<-->	IQ	4.131	-.034
e5	<-->	SQ	4.660	.028
e5	<-->	e61	6.332	-.046
e5	<-->	e60	4.654	-.036
e5	<-->	e29	8.605	-.067
e4	<-->	TS	5.593	.040
e4	<-->	e59	5.907	-.044
e4	<-->	e39	5.582	.051
e4	<-->	e35	4.079	-.045
e4	<-->	e10	4.093	-.049
e4	<-->	e5	6.071	.046
e3	<-->	e54	4.941	-.030
e3	<-->	e51	6.936	.037
e3	<-->	e20	5.234	-.044
e3	<-->	e13	4.519	.040
e1	<-->	e24	4.651	.046
e1	<-->	e21	6.752	-.063
e1	<-->	e5	5.083	-.043

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality

- **Standardized Residual Covariances (Group number 1 - Default model)**

	DQ1	DQ2	DQ3	DQ4	IQ1	IQ2	IQ3	IQ4	IQ5	IQ6	SQ1	SQ2	SQ3	SQ4	SQ5	SQ6	SQ7	SQ8	SQ9	UP1	UP3	UP2
DQ1	.00																					
DQ2	2.52	.00																				
DQ3	-.68	-2.27	.00																			
DQ4	-.42	-.32	.84	.00																		
IQ1	-1.31	-.52	1.29	-.13	.00																	
IQ2	-.20	1.15	.54	-.51	.43	.00																
IQ3	-.27	.56	.47	.09	.23	2.48	.00															
IQ4	-.99	.23	1.30	-.38	-.52	-.49	-.48	.00														
IQ5	-1.00	-.47	2.32	-.08	-.17	-1.26	-1.96	1.74	.00													
IQ6	-.37	-.30	1.16	.58	.22	-1.38	-.67	.14	1.45	.00												
SQ1	-.98	-1.06	2.13	-.96	-.05	-.45	.20	.31	.45	.28	.00											
SQ2	.02	.86	2.01	-.94	-.91	-.99	-.31	.30	.05	-1.20	-.27	.00										
SQ3	-.57	.14	1.87	-.60	-.56	-1.06	.02	.28	.28	-.23	-.39	1.19	.00									
SQ4	-1.34	.21	1.91	-.84	-.76	-1.41	-.12	.28	-.16	-.56	-.32	.63	.58	.00								
SQ5	-.11	.59	2.82	-.27	-.33	-1.08	-.27	.24	.18	-.56	-.36	-.17	.33	.06	.00							
SQ6	-.47	.12	2.09	.03	.18	-.03	.66	.57	.11	-.15	.48	-.34	-.71	.11	-.05	.00						
SQ7	-1.28	-1.06	2.65	-.76	.39	-.33	.44	.93	.86	.07	.59	-.93	-.17	-.71	.16	.48	.00					
SQ8	-.29	-.22	2.75	-.60	.73	.64	1.31	1.19	1.78	.17	.05	-.03	-.41	-.07	-.10	-.03	.33	.00				
SQ9	1.50	.56	1.79	-.30	.90	2.03	.65	1.72	1.03	1.22	-.03	-.28	-.89	-.26	-.10	.65	.36	-.13	.00			
UP1	-.95	.48	1.37	.56	-.25	.49	1.00	-.26	-.04	.34	1.02	1.08	.99	.35	.78	.85	.01	1.78	-.53	.00		
UP3	-.70	.24	.40	-.77	-.60	.90	.73	-.96	-1.16	-.29	-.97	-.87	-1.31	-1.01	-1.64	-.81	-1.67	-.07	.05	.02	.00	
UP2	-.38	.50	.93	-.23	.10	1.54	1.38	-.28	-.60	-.27	.71	.68	.06	-.03	.54	.82	.40	.94	.66	-.24	.19	.00
T1	-.80	-.52	2.40	-.05	.12	-.02	.62	.98	.73	-.08	.11	.50	.32	.58	.79	.04	-.22	1.43	.34	-.19	-.73	-.38
T3	-.10	-.88	1.96	-.12	-1.12	-1.14	-.26	.21	.38	-.70	-.54	-.67	-.58	-.91	-.23	-.87	-.54	.37	-.39	1.21	.15	.01
T2	-1.77	-1.07	1.60	-.20	.28	-.87	.02	.92	.66	.45	.38	.24	.14	.00	.39	.10	.38	.72	-.11	.05	-.16	-.23
ATT1	-.61	-1.12	1.05	-.25	-.19	.46	.70	.89	1.48	-.02	.22	.41	.50	.43	-.03	-.25	.06	.90	.22	1.05	.54	-.06
ATT4	-.44	-1.11	1.11	-.56	-1.18	-.53	-.26	-.14	.48	-.10	-.88	-.41	-.22	-.51	-.72	-.95	-.62	-.14	-.34	-.36	-1.42	.09
ATT3	.24	-.95	1.63	.40	-.30	.56	.70	.30	1.07	.42	.23	.76	1.05	.57	-.07	-.16	.40	.85	1.30	.47	-.45	.56
ATT2	.31	-.60	1.04	.00	-.79	-.55	.42	.17	.54	-.13	-.31	.69	.55	.05	-.04	-.36	-.06	.55	.62	.17	-.72	1.32
ITI1	-.63	-.33	1.41	-.21	-.65	.16	.44	-.22	-.87	-1.30	-.56	-1.04	-.40	-1.26	-1.37	-1.64	-1.70	-.84	-2.33	.40	-.24	-.47
ITI3	-.86	-.43	.38	-1.48	-.28	-.87	-.35	.97	-.03	.34	1.22	.15	1.76	.55	1.48	.76	.86	.93	.89	-.28	-1.25	-.39
ITI2	-.26	.67	1.80	1.44	.68	.44	1.11	1.12	-.17	.09	.60	-.03	.43	-.06	.14	-.07	-.21	.53	-1.39	.80	.16	1.90
DSS1	.57	.37	1.14	.08	-.20	-1.50	.14	.56	.20	.21	-.49	-.37	-.31	-1.21	-.13	-1.47	-.57	.21	-.62	.56	.03	.73
DSS3	-1.10	-.14	1.12	-.19	1.14	-.37	.27	2.11	1.58	.10	1.07	.97	.67	1.62	1.65	1.19	1.07	1.52	2.67	.19	-.57	.76
DSS2	.00	-.10	.17	-1.04	-.70	-1.90	-.75	-.01	-.68	-1.70	-.27	-.22	-.56	-.81	-.20	-1.56	-.88	.19	1.68	-.20	-1.63	.09
CHM1	-.66	-1.39	1.25	.46	.27	-.74	.99	.78	-.22	.32	.12	-.28	-.67	.14	-.28	-.21	.23	-.35	.75	.51	-.04	-1.00
CMH3	.21	-.63	1.05	.38	-.69	-.81	-.84	-.38	-.64	-.78	-.05	.21	-.60	-.06	.31	-.16	.38	-.64	-.36	.22	.03	-.12
CHM2	-.34	-1.41	.03	-.61	.57	-.02	.93	.89	.15	.07	.64	.30	-.16	.19	.13	.23	1.31	.24	.35	.55	.13	-.30
TS1	.36	-1.56	1.98	.74	.48	-.36	.48	-.08	.45	.61	.20	-.76	-.37	-.37	.50	-.13	-.27	.26	-.31	-.01	-.47	-.39
TS6	-.39	-.87	.15	-1.78	.13	-.42	1.06	.08	-.83	-.18	.20	-1.29	-.04	-.97	-.13	.01	.02	.87	-.73	.87	-.34	.70
TS5	-.09	-.93	1.34	-.53	.06	-.44	1.29	-.71	-1.02	.76	-.95	-.48	.37	-.22	.59	-.61	-.36	.12	-.72	.31	-.68	-.66
TS4	1.13	-.23	1.21	.64	.17	.32	1.11	.35	-.97	.68	1.99	1.24	1.83	1.81	2.07	2.30	2.41	2.72	3.87	.35	-.25	1.48
TS3	-.20	-1.22	.90	.42	.50	-.35	.94	-.40	-.61	.33	-.31	.29	.67	-.55	.78	.04	.32	.36	-.58	1.32	.33	1.45
TS2	-.29	-.13	1.68	.00	-.79	.00	.35	-.43	-.40	-1.65	-.88	-.79	-.56	-.48	-.14	-.33	-.12	.46	-1.53	-.60	-.81	-1.02
PM1	-.79	-.08	2.00	-.02	.69	.17	.10	.90	-.21	-.56	.65	-.21	.53	-.19	.12	-.10	.73	.47	.50	.48	-.12	.31
PM4	-.58	-.34	.52	-.37	-.65	-1.34	-.53	.11	-1.18	-.31	-.30	-.67	.14	-.17	-.42	-1.15	-.94	.24	-.49	-.18	-.48	-.85
PM3	-1.88	-.02	.06	-.14	.49	-.51	.86	.31	.53	1.20	.15	-1.10	.03	-.69	-.24	-.66	-.07	.36	-.69	1.07	-.11	.48
PM2	-.52	.90	1.85	.36	-.13	-.91	-.33	-.07	.38	.45	.32	.26	.66	.16	.25	.37	.62	.72	1.48	.39	-.77	-.19
R1	-.31	-.16	-.39	-.26	-1.04	-1.27	.54	.09	-.76	-.96	.08	-.43	-.47	-.30	-.41	-.82	-.85	.35	-.32	1.14	-.23	-.52
R3	.02	-.68	.96	.33	.53	-.34	.47	1.59	.29	.42	.75	.34	.33	.45	.40	-.03	.47	.95	.16	.21	-.83	-.70
R2	-.74	-.52	1.11	.17	-.12	-1.14	-.18	1.02	.61	.29	.14	-.46	-.17	-.22	.06	-.56	.12	.90	-.85	1.38	-.76	.47
CH1	.91	.25	2.32	-.33	-.17	.37	-.36	.20	.76	.69	.00	-.51	-.92	-.51	.20	-.91	-.63	-.19	1.32	.17	-.25	.93
CH5	.56	-.19	1.31	-.89	.03	.27	.38	.49	.33	.30	.27	-.71	-.52	-.05	.40	-.46	.03	.61	2.11	.04	-.83	.63
CH4	-.12	-.55	1.30	-1.13	-.90	-.23	-.73	-.24	-.09	-.47	.24	-.33	-.16	-.31	.22	-.19	.20	-.19	2.08	-.39	-1.24	.59
CH3	.00	-.49	.88	-1.27	-.70	-.15	-.50	.44	-.14	.08	.67	-.41	-.20	.20	.77	-.36	.27	-.15	.73	.30	-.26	.35
CH2	.78	-.01	1.27	-.40	-.38	.51	-.16	.69	.94	.49	.73	-.06	.18	.29	.20	.15	.91	.49	2.79	.49	-.83	1.10
MS5	-.45	.21	1.51	.06	.05	-.67	.01	1.40	1.68	.94	.07	.40	.44	.78	.30	.61	1.02	1.72	1.56	-.31	-1.49	1.07
MS4	-.46	-.58	.59	-1.10	-.88	-.85	-.20	.50	.23	-.94	-.68	-.66	-.98	-.43	.22	-.14	.20	.21	2.29	.24	-.25	1.10
MS3	-.15	-.64	1.54	-.55	.00	-.79	-.13	.67	.39	.01	-.11	-.36	-.90	-.51	-.64	-.41	.02	.62	1.58	-.72	-1.44	.09
MS2	.12	-.62	1.26	-.46	-1.11	-1.53	-.46	-.22	.28	-.65	-1.28	-.76	-1.30	-1.10	-.73	-.70	-1.10	.41	.67	1.01	.16	1.42
MS1	-.06	.36	1.99	.02	.10	-.20	.37	.92	1.34	.64	.57	1.12	.57	.39	.88	.89	.51	.72	2.41	.39	-.50	.91
BPV5	-.88	-.24	1.63	-.82	-.79	-.70	-.85	-.69	-.84	-1.56	.37	.27	.22	-.32	.41	.08	.23	.89	1.91	-.09	-.57	-1.20
BPV4	-1.05	.01	2.11	-.16	.64	1.59	1.43	-.15	.56	-.05	.76	.42	.70	.47	1.34	.47	1.03	1.85	1.65	1.50	.93	.67
BPV3	-1.27	-.42	2.03	-.14	-.12	1.20	.45	.50	-.76	-1.03	-.04	-.07	-.62	-.24	.31	.23	-.38	.40	1.70	.46	-.38	-.36
BPV2	-1.03	.49	1.90	.14	-.22	1.16	.87	.24	-.37	-.97	-.38	-.33	-.52	-.84	.23	-.73	-.84	.14	.79	.19	-.25	-.43
BPV1	-1.16	.32	1.06	-.28	.29	1.46	1.42	.36	-.14	-.15	.24	-.14	-.68	-.59	-.14	-.28	-.02	-.08	2.12	.25	.10	.61

	T1	T3	T2	ATT1	ATT4	ATT3	ATT2	ITI1	ITI3	ITI2	DSS1	DSS3	DSS2	CHM1	CMH3	CHM2	TS1	TS6	TS5	TS4	TS3	TS2
T1	.00																					
T3	-.07	.00																				
T2	-.16	.22	.00																			
ATT1	.56	-.06	-.02	.00																		
ATT4	-.28	-.99	-.75	-.25	.00																	
ATT3	1.31	.70	.13	.31	.07	.00																
ATT2	1.08	-.86	-.30	-.03	.47	-.62	.00															
ITI1	-1.03	-.21	-.29	-.87	-1.49	.45	-1.18	.00														
ITI3	-.25	-.29	.90	.35	.42	1.28	.42	.06	.00													
ITI2	.85	-.03	.69	.01	-.41	.88	.26	.61	-.65	.00												
DSS1	.20	-.58	.53	.20	-.06	-.02	1.07	-.53	.27	.79	.00											
DSS3	.11	.34	.55	.52	-.41	.03	.92	-1.33	-.27	.15	-.30	.00										
DSS2	-.14	-1.12	.20	-.82	-1.23	-.68	.18	-.16	.09	1.32	.48	-.15	.00									
CHM1	.19	-.02	.19	-.08	-1.01	1.00	.31	-.15	1.66	.47	-.15	.57	.34	.00								
CMH3	-.29	-.58	.09	.26	-.98	.53	.11	-2.07	-.06	-.96	-1.63	.26	-.96	-.02	.00							
CHM2	.16	.00	.30	.40	-1.03	1.06	.17	-.76	.74	-.03	.86	.47	.64	-.05	.11	.00						
TS1	-.56	-.28	-1.25	-.51	.01	.91	-.69	.51	.25	.09	-.08	.26	-.06	-.04	-1.16	-.06	.00					
TS6	-.59	.66	.06	-1.33	-.47	.77	-.72	.08	.28	-.19	-.47	.13	.98	1.61	.55	1.20	.62	.00				
TS5	-.15	.30	.54	.25	.13	1.91	-.12	-.12	-.38	-.45	-.15	-.76	-.81	.10	.53	.07	-.31	-.16	.00			
TS4	-.27	.70	1.76	1.47	.29	1.94	.90	-.18	.20	.25	-.10	1.41	.10	-1.15	-.57	-.65	-.55	.30	-.13	.00		
TS3	.10	.38	-.14	-.95	-1.47	.76	-.92	-.17	-1.50	.69	1.12	.35	.24	-1.11	-1.16	.27	-.61	-1.07	1.27	.71	.00	
TS2	.11	.73	-.54	-.56	-.54	.73	.55	.75	-.14	-.01	-.61	-.40	.05	-.24	-.07	.38	.61	.04	-.59	-.49	.29	.00
PM1	1.03	.94	.79	-.05	-.74	.64	.05	.49	1.38	1.74	.34	.98	.06	1.00	1.14	.43	-.54	.93	.39	.53	-.14	-.15
PM4	-.09	-1.12	-1.06	.28	-.19	.74	-.41	-.71	.41	-.24	-.10	.44	-1.33	.11	-.22	.07	-.63	.76	.66	.73	-.52	-.17
PM3	.20	.09	-.55	.14	.03	.59	-.08	-.94	-.25	.20	-.61	-.16	-1.82	-.51	-1.76	-1.43	-.43	.73	-.13	.55	.30	.06
PM2	-.02	-.31	-.26	-.23	-.35	.10	-.21	-1.41	-.25	-.75	.64	1.57	-.99	-.01	-.08	.27	-.78	-.30	-.09	-.22	.17	-.59
R1	.02	-.19	-.16	.36	-.41	.29	-.47	-.99	.92	-.61	-.58	-.10	-.09	.37	-.42	-.57	-.45	.83	-.09	1.82	.15	-1.04
R3	.61	.21	-.57	.59	-.68	.38	-.18	-.88	1.06	-.04	-.23	.49	.56	.29	.14	-.93	-.20	.38	-.34	.73	-.06	-.67
R2	.16	-.05	-.16	.98	-.38	.47	-.21	-.76	.71	.47	.16	-.09	-.03	.48	-.24	-.11	.29	.72	-.35	1.06	.54	-1.22
CH1	1.18	-.74	-.20	.03	-1.01	.07	.10	-.62	-.61	-.66	-.79	.09	-1.25	-.61	-.10	-.98	-.27	.01	.03	.18	-.05	-.83
CH5	-.08	-1.17	-.43	.51	-1.90	-.06	-.54	-.78	-.34	-.11	-.21	.97	-.49	-.26	-.03	.10	-.15	.41	-.24	2.09	-.38	-.36
CH4	.21	-.50	.32	-.17	-1.32	.37	.15	-.43	.89	.06	-.01	1.03	-.17	.03	-.07	.12	-.26	1.25	.24	1.15	-.13	-.37
CH3	1.02	-1.25	.31	-.03	-.17	.02	.30	.07	.63	1.28	.00	.55	-.18	1.00	.64	.48	.21	1.02	.41	.57	.22	.45
CH2	.91	.11	.64	.82	.40	1.78	1.53	-.65	1.29	.23	.36	.60	-.49	.18	-.52	.04	-.97	.26	-.61	1.58	-1.32	-.74
MS5	.71	-1.24	1.15	-.09	.39	1.43	1.28	-.25	.79	.63	.75	1.12	-.80	-.05	-1.12	1.19	.29	.52	.44	2.87	.60	-.56
MS4	.48	-.59	1.19	-.39	-.04	.61	1.00	-.41	1.08	1.12	-.04	.92	-.25	.48	.48	1.32	.64	.31	.84	3.16	.83	.12
MS3	.53	-.80	.80	-1.75	-.60	-.06	.03	-1.25	.40	-.10	.07	1.43	.66	-.28	-.91	.08	-.66	.44	-.94	1.75	-.40	-.59
MS2	.93	-.94	.55	-1.99	-.79	.08	.03	-1.23	-.30	.32	-.93	-.37	-.99	.33	.14	.29	-.67	1.11	-.10	1.22	.16	.04
MS1	-.39	-.99	-.23	-.78	.10	.91	.18	-.82	.32	.10	-.77	.21	-1.48	-.17	-.54	-.13	-.35	-.78	-1.41	1.51	-1.17	-1.46
BPV5	-.27	-.63	-.23	-1.21	-.69	-.01	.10	.15	-.18	-.71	-.39	-.78	.00	.16	-1.48	-1.47	.32	.12	.64	-1.39	-.23	-1.18
BPV4	1.22	-.01	.82	.53	.86	2.30	.98	.55	.30	-.43	.79	.01	.87	.95	-.80	.22	1.44	.41	1.82	-.13	1.59	.60
BPV3	-.05	-.07	.36	-.88	-.52	.15	-.37	.00	-.17	-.12	-.19	.01	-.18	1.31	-.51	.08	.05	-.28	.51	-.75	-.35	-.95
BPV2	.39	-.31	-.33	-.23	.18	.77	.14	.57	-.39	.35	.31	.19	.16	.12	-1.16	-.14	-.04	-.47	.58	-1.42	-.34	-.78
BPV1	.57	-.23	-.43	-1.20	-.42	.23	-.24	.02	-.32	.41	-.47	.22	-.39	1.18	-.29	.94	.04	.05	.72	-1.41	1.02	-.76

	PM1	PM4	PM3	PM2	R1	R3	R2	CH1	CH5	CH4	CH3	CH2	MS5	MS4	MS3	MS2	MS1	BPV5	BPV4	BPV3	BPV2	BPV1
PM1	.00																					
PM4	-.14	.00																				
PM3	-.21	.36	.00																			
PM2	.00	.09	-.04	.00																		
R1	-.08	.74	.59	.05	.00																	
R3	.26	-.09	-.53	-.03	.05	.00																
R2	-.26	-.70	-.10	.14	-.01	-.05	.00															
CH1	-.57	-.64	-.68	-.66	-1.07	-.16	.23	.00														
CH5	.54	-.32	-.02	-.17	-.23	-.40	.08	.32	.00													
CH4	1.51	-.21	.93	.88	-.33	-.41	.49	-.15	-.13	.00												
CH3	.61	-.22	.22	-.37	.12	.17	.42	.43	-.15	-.26	.00											
CH2	.61	-.70	-.04	-.46	.08	.68	.53	-.38	.00	.43	-.14	.00										
MS5	.16	.04	-.01	.70	.23	-.80	.20	-.45	-.26	-.26	-.55	.26	.00									
MS4	-.17	.19	-.55	.13	1.27	.49	1.46	.15	-.47	.42	.21	.11	-.11	.00								
MS3	.05	-.02	-.25	-.16	.03	-.68	-.76	-.39	-.31	.70	-.04	.38	-.37	.02	.00							
MS2	-.01	-.39	-.10	-.47	.55	-.10	-.06	.20	.06	.49	.11	.16	-.46	.32	.64	.00						
MS1	.16	-.52	.07	1.01	.01	-.96	-.06	-.17	-.18	-.07	.09	-.08	.56	-.26	-.09	-.28	.00					
BPV5	-.15	-.72	.03	.09	.12	.26	.88	-.96	.01	-.13	.52	-.06	-.19	-.41	-.47	-1.31	-1.16	.00				
BPV4	.79	-.51	.59	.43	.79	-.04	1.03	.49	.66	1.10	1.05	.43	.41	1.60	.91	.77	.61	.55	.00			
BPV3	.78	-.21	-.23	.04	-.45	-.78	.69	-.15	.24	.75	.36	.23	.99	.71	.49	.13	-.08	.07	-.29	.00		
BPV2	-.07	-.41	.22	-.55	-.28	-1.11	.01	-.84	-.66	-.66	.16	-.54	.02	-.11	-.55	-.32	-.92	-.06	-.27	.08	.00	
BPV1	.21	-1.12	.80	.84	.30	.17	.90	-.36	-.01	-.20	.37	.52	.52	.64	.23	-.05	-.06	-.54	-.08	.08	.32	.00

BPV: Business plan and vision, **MS**: Management Support, **CH**: Champion, **R**: Resources, **PM**: Project Management, **TS**: Team Skills, **CHM**: Change Management, **DSS**: Data Source Systems, **ITI**: Information Technology Infrastructure, **ATT**: Attitudes toward Technology, **T**: Trust, **UP:** User Participation, **SQ**: System Quality, **IQ**: Information Quality, **DQ**: Decision Quality