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Factors influencing the quality of decision making using business intelligence in Hulamin-KZN

Annesh Singh

200270749

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ABBREVIATIONS

BI	Business Intelligence
BIA	Business Intelligence and Analytics
BA	Business Analytics
BDA	Big Data Analytics
CSFs	Critical Success Factors
DSS	Decision Support System
DW	Data Warehouse
ETL	Extract, Transform and Load
ERP	Enterprise Resource System
IS	Information System
IT	Information Technology
MIS	Management Information System
OLAP	Online Analytical Processing
OLTP	Online Transactional Processing
ROI	Return on Investment
DIKW	Data Information Knowledge Wisdom
TDWI	The Data Warehouse Institute
TAM	Technology Acceptance Model
DQ	Data Quality
IQ	Information Quality
IoT	Internet of Things
CPS	Cyber Physical Systems
RBV	Resource Based View

ABSTRACT

The current study sought to investigate the factors that affect decision-making by use of business intelligence (BI). Specifically, the study was focused on information quality, system quality and BI service quality. Business intelligence uses organisational data, performs analytical functions and provides decision makers with high quality information to support decision-making. This quantitative study, based on the researcher's experience of BI, was carried out in a selected manufacturing organisation which recently implemented business intelligence in KwaZulu-Natal. The study used a self-administered survey sent out to participants who used business intelligence so as to gather data on their perception of these variables on the quality of decision-making. All the employees of the organisation with sufficient report runs made the population of the study. The collected data came from different levels of employees, namely managers (47%) and non-managers (53%) with varying levels of BI experience. The results were imported into SPSS for analysis. The data showed that information quality had a positive significant impact on the quality of decision-making; system quality had a positive significant impact on the quality of decision-making; and BI service had a positive significant impact on the quality of decision- making. Thereafter, a conducted multiple linear regression analysis to determine the strength of these variances in influencing decision-making revealed that the three variables explained 65.7% of the variance in the quality of decision-making. Overall, the study found that high quality information, coupled with a high-quality system and good BI service, leads to a higher quality of decision-making, and that the impact of BI on decision-making is positive. This finding concurs reviewed literature.

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CHAPTER ONE: INTRODUCTION

1.1. Introduction

Business intelligence (BI) does not have a formal definition, but is generally considered as an umbrella term encompassing a mix of product, technology, processes and people to transform data from multiple sources into meaningful information that is used to support decision making (Chee, Chan, Chuah, Tan, Wong and Yeoh, 2009, Negash, 2004, Vinaja, 2016, Watson, 2009). It was argued that BI focused on using past data to help businesses focus on performance metrics whilst business analytics focuses on generating new insights and predicting outcomes, however now the more favourable term is big data analytics which includes both structured and unstructured data that is in high volume analysed in real time (Krishnamoorthi and Mathew, 2018, Wazurkar, Bhadoria and Bajpai, 2017). However, for the context of this study, the terms 'business analytics', 'big data analytics' and 'business intelligence' will be used interchangeably since the focus of this study is on decision support.

Many companies realise the importance of business intelligence and the role it plays in competition. There is a significant increase in academic papers and practitioners offerings (Bayrak, 2015). According to Gartner (2017), the BI and analytics market is becoming increasingly central and by 2020 will yield a market share of $22.8 billion.

Business intelligence (BI) can play a significant role in gaining competitive advantage (Davenport and Harris, 2017), although it is not well understood how the BI investment creates business value (Krishnamoorthi and Mathew, 2018). The partial causal relationship between information systems (such as BI) investments and business value remains unconfirmed and is believed to be an ongoing subject of research for information system researchers (Schryen, 2013).

There is an expectation that managerial experience combined with BI tools will increase the quality of decisions in organisations. However, various researchers have revealed that BI has, on several occasions, failed to provide value in organisational projects. This failure has been linked to technical issues, poor data quality or organisational issues (Colas, Finck, Buvat, Nambiar and Singh, 2014, Lupu, Bologa, Lungu and Bra, 2007, Nelson and Todd, 2005, Visinescu, Jones and Sidorova, 2017, Watson and Wixom, 2007). A recent report by the McKinsey Global Institute using survey data from several United States of America (USA) company executives showed that companies only harnessed a fraction of their data and analytics value (Henke, Bughin, Chui, Manyika, Saleh, Wiseman and Sethupathy, 2016) due to the limited analytical capability of these organisations. This finding is supported by several studies (Akter, Wamba, Gunasekaran, Dubey and Childe, 2016, Tai, Wang and Yeh, 2018). BI, when done right, can result in better decisions, increase profits and effectiveness, of organisations. When not done properly, BI can be expensive and a waste of resources and time (Bayrak, 2015, Williams and Williams, 2010).

The manufacturing industry is going through a radical transformation known as industry 4.0 which gives rise to smart manufacturing whereby technologies such as IoT (internet of things) and CPS (cyber physical systems) are emerging, this can create large amounts of data which may be difficult to analyse by use of traditional BI methods. This is because these methods require data to be processed in real-time in order to ensure that quality decisions are made in time within and across organisations (Janssen, van der Voort and Wahyudi, 2017, O'Donovan, Leahy, Bruton and O'Sullivan, 2015). However, there is little research about the use of big data and its impact on decision making (Janssen et al., 2017).

1.2. Motivation for the Study

There is limited literature on the role of business intelligence applied within organisational structures. There has been an increased mobilisation by various research organisations for the need by researchers to produce more publications on how business intelligence can be deployed within organisations to influence decision making (JOCEC, 2017). Scholars such as Trieu (2017), reviewed empirical studies which explored the BI organisational value and found that there was a general lack of studies in this area. The reviewed literature suggests that future research should focus on lifecycle processes comprising of BI investments meant to positively impact on organisational performance. There is a lack of research showing how business intelligence is used to improve the quality of decision making in organisations (Cao, Duan and Li, 2015, Janssen et al., 2017). In addition, the literature focusing on BI success has had a tendency of overlooking decision making quality(Visinescu et al., 2017).

The study will provide insights into factors influencing BI use and decision-making quality within the organisation, it will highlight possible recommendations which will improve the overall business value.

The study could create an assessment instrument used to gauge the impact of BI on decision-making quality, specifically in a South African manufacturing space. The practical benefit of the study could be to guide managers and practitioners embarking on a BI implementation, on how to better utilise expensive resources and to focus on key activities within key areas that would create value within organisations. The assessment instrument could be used as a yardstick to measure the current impact of BI and could point out on aspects which need to be improved.

1.3. Focus of the study

The study was conducted in a public company - Hulamin – which is headquartered in Pietermaritzburg, KwaZulu-Natal, South Africa. It is a semi-manufacturing aluminium rolling plant listed on the JSE, and it deals with rolled coils which are meant for both local and international consumer conversation organisations that create end products such as vehicles, aluminium beverage cans, foils, cookware, and extruded aluminium products, to mention only a few. The study focused solely on the on the Pietermaritzburg site, specifically on BI users (those employees whom have access to the BI systems) as the study seeks to understand how through the usage of BI does certain factors influence the quality of decisions, therefore a certain level of usage is required.

Hulamin recently implemented a business intelligence programme. A dedicated business intelligence team falling under the information technology department followed a phased implementation approach which first focused on key departments but which has since then extended to other departments.

1.4. Problem Statement

Organisations have a burden to create value which will eventually result in financial gain for all the actors. However, measuring BI value against the investment costs or measuring how long it will take before BI products have been converted to financial gain remains a challenge (Elbashir, Collier and Davern, 2008, Jourdan, Rainer and Marshall, 2008). Several theories such as technology acceptance models and diffusion of innovation models explain factors that affect technology adoption and diffusion through different departments. However, there is limited literature focusing on BI post-implementation adoption and how it affects decision making (Côrte-Real, Ruivo and Oliveira, 2014, Deng and Chi, 2012, Verma, Bhattacharyya and Kumar, 2018).

Decision quality is ultimately a function of effectiveness and efficiencies in decision making process. Whilst there is no absolute measure for it, available studies often consider the decision making process as a surrogate of decision quality (Visinescu et al., 2017). This is the approach followed by this study.

The business value of the BI investment in Hulamin is unmeasured and its value to quality of business decisions is currently vague. This could indicate that the adoption of the BI system is still in its infancy and yet to be pervasive across the organisation. Thus, according to Davenport and Harris (2017)'s analytics maturity model, the company is still in the descriptive stage. It is thus not yet mature enough to be considered an analytical competitor.

It is unclear how or which factors influence decision making quality or how this can be improved to ensure well informed and timeous decisions (Janssen et al., 2017). The overarching problem of the study is based on the premise that the value of BI is currently vague and widely misunderstood. However as noted in maturity theories (Davenport and Harris, 2017), the organisation progresses from making decisions intuitively to becoming a data-driven or an analytical organisation.

One of the leading challenges that BI implementations face, is to ensure that high quality information is transferred into outputs of BI assets for decision making, and currently, there is very little literature addressing the role of information quality and system quality in successful BI implementation (Dooley, Levy, Hackney and Parrish, 2018).

The study seeks to understand how factors influence the quality of decision-making using business intelligence.

1.5. Research Hypothesis

The hypotheses of the study are:

I. H_1 Information Quality has a positive impact on the quality of decision-making using BI.
II. H_2 System Quality has a positive impact on the quality of decision-making using BI.
III. H_3 BI Service Quality has a positive impact on the quality of decision-making using BI.

1.5.1. Null hypothesis

I. H_0 - Information quality has no influence on the quality of decision-making using BI.
II. H_0 - System quality has no influence on the quality of decision-making using BI.
III. H_0 - BI service quality has no influence on the quality of decision-making using BI.

1.6. Objectives of the study

The objectives are as follows:

1.6.1. Primary objective

1. To investigate the factors influencing the quality of decision-making using business intelligence in Hulamin-KZN.

1.6.2. Secondary objectives

2. To determine if information quality has a positive impact on the quality of decision-making using business intelligence in Hulamin-KZN.
3. To determine if system quality has a positive impact on the quality of decision-making using business intelligence in Hulamin-KZN.
4. To determine if BI service quality has a positive impact on the quality of decision-making using business intelligence in Hulamin-KZN.

1.7. Research Methodology

This is a quantitative study. It used a cross-sectional self-administrated online survey questionnaire using a sample of 43 users from the active BI user population. A descriptive research design method was employed to test the influence of independent variables (such as BI service quality, data quality and information quality) on the dependant variable (quality of decision-making). The questionnaire was based on a five-factor Likert scale. The results from the survey were analysed using a statistical package SPSS with Spearman's rank correlation analysis to establish correlations amongst variables. In addition, inferential and descriptive statistics were utilised.

1.8. Chapter Outline

The study is organised into five chapters summarised as follows:

Chapter One: Introduction

The first chapter of this study provided the background of the company being studied, the focus and motivation for the study, expected outcome and limitations.

Chapter Two: Literature Review

Chapter two presents the literature that is related to the study. It provides examples of the benefits and reviews existing theories on factors of BI that affect the quality of decision-making.

Chapter Three: Research Methodology

Chapter three explains the research methodology that was used, and details how the study and analysis was done.

Chapter Four: Data Presentation and Analysis

Chapter four presents the data that was gathered in the study using the research methods discussed in Chapter Three.

Chapter Five: Conclusions and Recommendations

Chapter five concludes the study and makes the major conclusions.

1.9. Conclusion

Chapter one provided an introduction to the study. It outlined the problem statement. The objective of the study was to determine if factors such as information quality, BI service quality and system quality positively influence both the BI usage and improve the quality of decision making. This is important both for management and the BI team as it provides insights on how BI impacts decision making. The assessment instrument can also be used as part of a continuous improvement tool to gauge the impact on decision making, and focus on specific areas for improvement.

CHAPTER TWO: LITERATURE REVIEW

2.1. Business Intelligence

Competition in the 21st century is the fiercest, with competitor companies quickly copying technologies and processes thus leaving little to optimize in terms of cost savings therefore many companies are turning to analytics to harness their data to gain valuable insights which are used to compete in a dynamic environment (Davenport and Harris, 2017).

An information culture refers to shared beliefs, attitudes and values of the employees within a single organisation. Power (2016) explains that a company's information culture can be one of four information cultures: (i) a company that observes changes in the market and does nothing is called the spectator, (ii) a company that initiates change and thus influence markets is called the competitor, (iii) a company that attacks the market principles is called a predator and (iv) a company that is disorganised and experience a dysfunctional view of information is called information anarchy.

A data-driven culture conforms to Tanler's competitor culture as it is concerned with fact or evidence based decisions and has in place processes that support this type of decision making. Thirathon, Wieder, Matolcsy and Ossimitz (2017) conclude that from their study that firms with higher analytical culture was the main driver analytical decision-making and were more competitive.

The resource based view suggests that the qualities and arrangement of resources makes the firm distinctive from a competitive perspective, resources must be valuable, rate, inimitable and non-substitutable (Ji-fan Ren, Fosso Wamba, Akter, Dubey and Childe, 2017). The central tenant of the resource based theory is the quality of resources and a firm's capabilities, thus a data-driven culture is a key competitor capability (Davenport and Harris, 2017).

Data driven analytical firms include Amazon which harnessed big data to disrupt the conventional book industry and become a leader in online shopping, Google exploited data from its search engine to provide personalized advertising based on individuals preferences, Facebook also used personalized data to serve customer preferences, General electric used real-time analytics and the cloud to create an application called Predix which scheduled maintenance based on real-time data thus improved machine efficiency and reduced downtime (Vassakis, Petrakis and Kopanakis, 2018).

2.1.1. Information as an asset

Drucker and Wilson (2001) state that businesses generate data not information. Ackoff (1989) first introduced the 'hierarchy', see Figure 2.1-1 DIKW hierarchy (aka. Information Hierarchy/knowledge pyramid). In his original works, there was a sixth level called understanding. However, it was later revised to be inclusive in the four levels. Each of the levels is explained by the categories or levels below it. Thus, wisdom is only attained *via* knowledge, and knowledge attained *via* information, and information is attained from data.

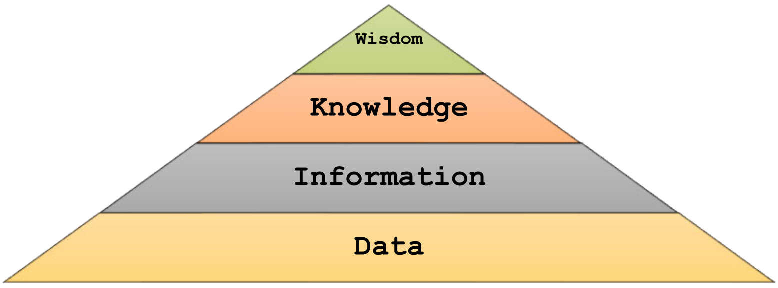


Figure 2.1-1 DIKW hierarchy (aka. Information Hierarchy/knowledge pyramid)

Rowley (2007) summarizes the levels of the pyramid as follows: (i) data which is the lowest level, comprises of attributes of objects or events. It is said to be the true value (facts) or measures from instruments (observations), however, without context, it is essentially meaningless. (ii) Information level which lies above data is processed data, it is classified, formatted or arranged to form meaningful descriptions. It provides a context for data, and answers the basics of questions such as who, what, where, when and how many. (iii) Knowledge lies above information in the pyramid however it remains an ambiguous and an elusive concept. Knowledge is a combination of data and information which leads to explanation and formation of instructions. It provides answers to 'why' questions. Knowledge is divisible into explicit knowledge and tacit knowledge. Explicit knowledge is knowledge that can be recorded into databases whilst the latter is intuition, values, beliefs that cannot be recorded. (iv) Wisdom is at the apex of the pyramid, it is a subjective measure and thus seldom the same between two individuals. Wisdom requires values, and judgement.

A system is mechanism that accepts inputs and provides outputs for a certain purpose. An information system (IS) consists of several elements (hardware, software and data) working together to accept inputs and store (raw data), and then performs some transformations (processing) and disseminates the information (outputs) for a particular purpose (Stair and Reynolds, 2013). These computer systems have evolved in-line with hardware improvements; from simplistic calculators to complex learning systems capable of defeating human chess champions (Davenport and Harris, 2017).

Businesses are continuously infusing information systems into their business processes to better streamline and manage their everyday tasks to be more efficient and effective (Abai, Yahaya and Deraman, 2017).

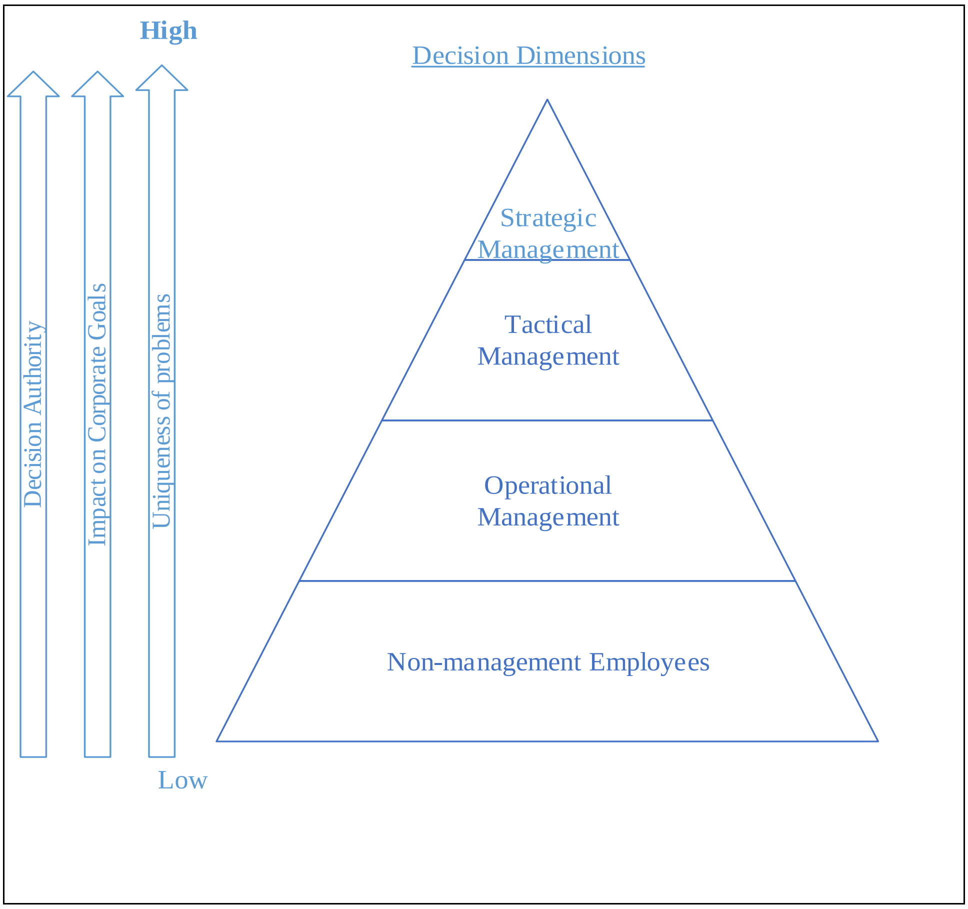


Figure 2.1-2: Management hierarchy of a typical organisation - (Stair and Reynolds, 2013)

The management hierarchy of a typical organisation consists of three levels, see Figure 2.1-2: Management hierarchy of a typical organisation - (Stair and Reynolds, 2013): operational level - consisting of workers executing operational plans (this is daily operations); tactical level - consisting of middle and upper management executing on tactical plans (this is short term plans), and strategic level - consisting of a few executives who must craft strategic plans for the organisation. As one moves further up the pyramid, the level of decision making becomes more difficult along with a greater impact on organisational goals. It also follows that problems at lower levels are often and are repeatable (non-unique) whilst unique problems at strategic levels.

2.1.2. What is Business Intelligence?

In 1989, Business Intelligence (BI) was first mentioned by Howard Dresner of Gartner Group. The concept is related to both concepts and methods related to improving decision making using fact-based support systems. However, it was later found that Luhn in 1958 in an IBM journal titled “A business intelligent system” the concept was first mentioned. However, the use of the concept by then was more general and was not deployed for purposes of decision making (Chee et al., 2009).

Business intelligence offers a comprehensive overall view of different business perspectives that support various analyses to solve current problems, and it acts as a tool to enable the business to rapidly react to changes in the organisational environment (Matei, 2010).

Some authors view business analytics as a radical tool to monitor and manage business activities and decision making; and facilitates a data driven culture, allowing firms to compete better (Davenport and Harris, 2017).

BI has been around for many decades, but there exists no formal definitions and no consensus among academics (Olszak, 2016). However, most cited definitions refer to an umbrella term encompassing a mix of technology, processes and people to transform data from multiple source systems into meaningful information that is used to support decision making (Negash, 2004, Vinaja, 2016, Watson, 2009).

A study reviewing several BI literature and definitions from various authors to reach a common definition of BI found that most definitions were still technology focused whilst others are process/business focused. It thus proposed that BI be considered as multi-faceted. In addition, the study presented three viewpoints to consider when defining BI (Chee et al., 2009). The technological viewpoint saw BI as a technology (hardware and software combination) that gathered, stored, consolidated, and analysed data to present “insights” for decision making. The emphasis was put on the technology and not on the process. The managerial or process viewpoint considered BI as a process; and emphasises management and coordination of the process from data production to consumption to support decision making. The product viewpoint was the last in the discussion, and it considered BI as a result (or high-quality data product) from analytical processing used to support decision making and performance management. The study proposed that a definition must consider all three viewpoints. This was supported by several studies that came later (Clavier, Lotriet and Van Loggerenberg, 2014, Olszak, 2016).

However, with technological advances in artificial intelligence and predictive analysis, there is a blur line between supporting decision making and automating decision making. BI also considered the use of past information to assist in present decisions. However, currently, analytics use past information to predict and automate future decisions. Thus, once again, the definition must be extended from supporting decision making to perhaps enabling decision making (Davenport and Harris, 2017, Wieder, Ossimitz and Chamoni, 2012).

BI as a product perspective must have characteristics such as integrated (enterprise wide view); data integrity (accurate and conforms to business rules); easily accessible, credible (single version of truth), and timely (available for decision making) (Chee et al., 2009). There is no consensus for the components of BI. A recent review of several articles included components such as knowledge management, decision support, dashboards, methodologies, processes analytics, competitive intelligence and big data (Olszak, 2016).

Olszak (2016), introduced three generations of BI eras: (i) BI 1.0 during 1970s – 1980s whereby statistical methods such as regression were employed on structured data. Toolsets consisted of SQL, OLAP and ETL (extract-transform-load). Reporting consisted of dashboards and scorecards; (ii) BI 2.0 during 1990 – 2005 whereby data mining, text and web analytics, advanced OLAP were employed on structured and textual data; (iii) BI 3.0 with predictive modelling, and technologies like mobile devices & RFIDs (radio frequency identification), unstructured data (images, videos, documents, social media posts) and Cloud BI offerings which reduces costs. The five attributes of BI 3.0 are (i) proactive (ii) real-time (iii) integrated with business processes (iv) operational and (v) beyond reach of organisations (Olszak, 2016).

2.1.3. Components of BI

Early systems compromised of specialised applications aimed at a departmental level addressing specific needs such as Financial Management Information Systems (FMIS), HRIS - Human Resource Information System, Material Requirements Planning (MRP1 & MRP2) and Computer Integrated Manufacturing (CIM). Each of these systems will maintain their own set of data, and there is no holistic organisation wide view of data. ERP systems addressed this issue by combining several modules using best practices into a single application with a consistent user interface which shared a single database (Hawking and Sellitto, 2010).

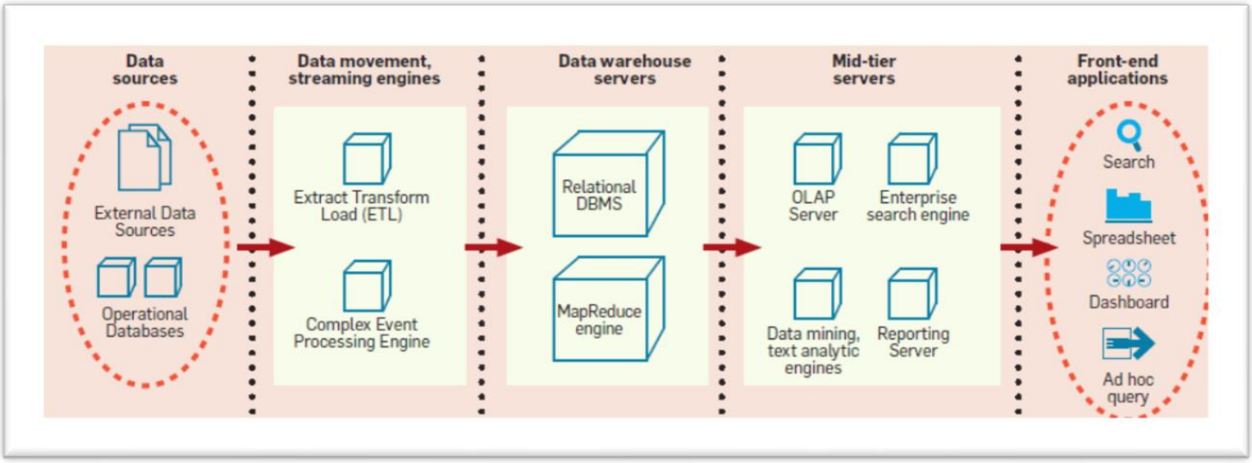


Figure 2.1-3: An example of a typical BI implementation (Chaudhuri, Dayal and Narasayya, 2011)

See Figure 2.1-3: An example of a typical BI implementation (Chaudhuri, Dayal and Narasayya, 2011), shows a graphical overview of a typical BI implementation in an organisation. Source systems provide data to data warehouses. Sources can be ERP systems, point of sale, web data, legacy system, spreadsheets or transactional databases. These source systems can be on different platforms, from vendors, customers, trading exchanges and internal systems. They store data in many different formats. It can be structured (such as XML, JSON) or unstructured (such as media types). ERP is a real-time transactional system with limited reporting functionality such that it can only report on data within the ERP and unable to report on consolidated data from the CRM for example or provide any insights on which data in CRM cause shifts in sales found in ERP. BI has an advanced analytical functionality which enhances the ERP system. Very few researchers looked at integration of ERP and BI. Nofal and Yusof (2013) found that it yielded several benefits such as automation of standard reports, reduced report generated time, increasing profits, reducing costs and facilitating data sharing. Since BI relies typically on data from ERP or other enterprise systems (termed source systems), it suffers several challenges such as poor decisions based on poor data quality captured in source systems (Yeoh and Koronios, 2010).

Extract-transform-load (ETL) is a set of tools that combine data from several unrelated data sources, apply rules including data cleaning mechanisms and load into the data warehouse. The most popular choice of implementing the data warehouse is the use of relational database management systems (RDBMS) which over the last two decades has seen many improvements to both storage retrieval and handling large volumes of data. Structured query language (SQL) is the most common language used to query, and interact with these RDBMS. It is a combination of English syntax, and uses operators such as (not, in, where, join, equals, sum, greater than and other mathematical operators) (Vinaja, 2016).

Chaudhuri et al. (2011) explains that online analytic processing (OLAP) allows end user to perform additional filtering, aggregation, pivoting and other operations to the exposed multidimensional view or data cube. Data mining is in-depth analytics that go beyond OLAP to recognise patterns and use sophisticated algorithms to even form predictive models which are useful for decision making. Reporting servers render reports to various outputs such as webpages, mobile, and other front-end applications

The increasing non-structured availability of data that business needs to analyse and respond to such as (emails, product reviews, social media data) brings focus to enterprise search engines and data mining especially text analytic engines to assist with this task.

Data integration services or data movement includes extract, transform and load services. Enterprise application integration services, enterprise information integration services and operation data feeds services. Data management services employ a variety of architectures, technologies and data models, including federated data marts, data warehouses, and OLAP cube data (Xia and Gong, 2014, Chaudhuri et al., 2011).

Mobile BI uses the capabilities of the smart phones to enable knowledge workers to access and make decisions on the go; with vendors of BI suites offering the BI application compatible for smart phones (Tutunea, 2015). Several popular front ends applications include: excel, dashboards, graphs and other ad hoc queries inform decision making.

Web analytics which provide information to businesses about the user activity on the websites such as number of visitors to each product page, and the use of Customer Relationship Management (CRM) software inform analytics and provide insight to the most popular products, and can even predict likelihood of most profitable products (Nam, Lee and Lee, 2018).

A collection of the tools is available for manipulating, mining and analysing the data for reporting *via* business performance management dashboards and scorecards. Finally, different information delivery tools and applications can communicate the BI to many different users including IT developers, analysts, information workers, managers, executives, front line workers, suppliers, and customers, the trend towards pervasive BI means extending the reach of the intelligence to other organisations (Chaudhuri et al., 2011).

2.1.3.1. Data at the right time – Big Data Analytics

Importance of timely and effective information is vital to the organisation’s survival. It leads to the difference of making a good and bad decision, and the consequences of the decision determine the weight of the reliance on the inputs (information) to the decision-making processes. Managers must not therefore rely on intuition to make decisions (Hočevar and Jaklič, 2008). Recently, there has been a growing interest in business intelligence. This was fuelled by lower hardware (parallel computational and data storage) costs and availability of cloud services, coupled with increasing data generated by businesses *via* devices (internet of things), RFIDs, emails, blogs, social media and websites to name a few. This has led to the 3Vs (volume, velocity and variety) data issues which recently has been extended to 7Vs (Vassakis et al., 2018) facing industry called the "Big Data" problem (Chen, Chiang and Storey, 2012, Suleiman, Al-Zewairi and Naymat, 2017, Verma et al., 2018). Data velocity is the increasing speed of data generation such as machine logs, clickstream data and data from devices. Data variety is vast formats of digital data structured and unstructured (media, text, video). Data volume is the large amount of data in bytes that need to be stored in datasets. Data variability is important for sentiment analysis (which is a technique to find out if something positive or negative was posted) in social media, it requires that the context of a sentence be taken to infer the meaning of the word, as a word could mean several things but without context the meaning is lost (Vassakis et al., 2018). Data veracity refers to how reliable and accurate the output from the process of data collection is. Data visualization is a science of presenting both qualitative and quantitative data in intuitive formats that are easy to spot patterns, trends and anomalies at a glance (Vassakis et al., 2018).

Big data differs in that traditional methods to store and analyse data are not sufficient for big data because of large volumes and different formats (non-structured).

Newer operating systems supporting larger data stores (such as 18 Exabyte's (EBs) in windows server 2016) coupled with the significant drop in costs per megabyte of memory and faster parallel processors leads to an effective in-memory analytical store supporting close to real time querying. MapReduce are engines that were specifically designed for web search logs. These engines are increasingly being used in conjunction with Hadoop (open source parallel processing technologies) by businesses to handle "Big data" issues. Cloud providers offer scalable big data solutions at fractions of the costs of owning one (Balachandran and Prasad, 2017). There is an increasing need to react and make instant decisions based on operational data in near real time. These are referred to as Complex Event Processing (CEP).

The term 'real-time' business intelligence which means instantaneous is misused. Data users prefer "right time" as there is a lag between data that has been captured and the data that has to been reflected in the data warehouse. This lag is done for several reasons namely; costs and performance reasons (Hackathorn, 2004).

There is always a lag between the occurrences of business events and the action response to that event. A real-time system in engineering terms is measured in milliseconds for a system to respond. However, in business scenarios, elapsed time between the event and action spans minutes, hours and days. Data latency is the time it takes for ETL (extract, transform, load into data warehouse) to reflect. Analysis latency is the amount of time spent to study the event; and decision latency is the elapsed time for a decision maker to understand the event and then react accordingly. For automated systems where no human input is required, response can be immediate.

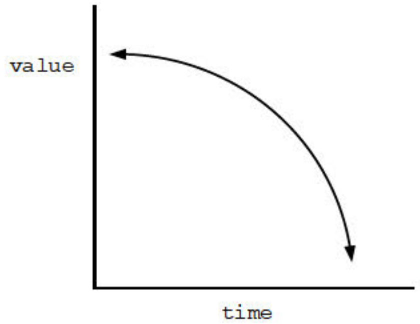


Figure 2.1-4: inverse decay curve showing value of information over time

The inverse decay curve (see Figure 2.1-4: inverse decay curve showing value of information over time) shows that the value of the data based on the circumstances or the context decreases over time. The maturing value curve shows that the value increases over time. The perishable value curve shows that up until a certain point value, is valid, however, once past this, it is of no value. Generally, for most competitive businesses, information context resembles the inverse decay curve (Hackathorn, 2004).

Data slowly decreases in quality until it is eventually stale. Eckerson (2002) showed that textual data suffers from this as well. As shown in a data store of persons whereby last names were shown to be stale after a few years due to changes in last names and addresses, numeric data also suffered degradation in terms of time-value of money.

2.1.3.2. Predictive Analytics

Predictive analysis has been very useful in companies such as Google, Amazon, Facebook and Netflix whereby specific targeted user advertisements lure customers and improve profitability; it's also been proven to work well and insurance industry is whereby a person's health will give a better risk or which improves cost and quality healthcare (Wazurkar et al., 2017). Predictive analysis is a process to predict behaviour of the future but trying to find patterns using algorithms in the data.

Figure 2.1-5: Process of predictive analysis

Wazurkar et al. (2017) introduced the process for predictive analysis, it consists of several steps (see Figure 2.1-5: Process of predictive analysis), the first step is identifying the business goals for example predicting similar items when the customer adding a single item to shopping cart. The second step in the process is data understanding from various sources, these sources can be from government data, social media and websites. Data visualisation tools help to explore the data from various sources and data scientists can determine which ones are relevant for the purpose. Data preparation is the next stage this is the biggest challenge as analysts must try and pre-process the data to get it ready this involves data cleansing. Development of the predictive model involves choosing among several artificial intelligence and learning algorithms using modelling tools to conduct analysis to find the best model to fit the need. Evaluation of the model is important to ensure a good fit, this is done by setting up a benchmark which could be a random model which is used to compare the predictive model against, if it's better than the random model it could be good enough for predictive analysis. If no model matches, the data is not suitable for predictive analysis. The last step is deployment whereby rules to acquire data and constraints are supplied. It is important to continuously evaluate and adjust the model to ensure that the model is still valid and meets the changing needs.

2.1.4. Benefits of BI

Benefit(s)	Sources
Increased profits via business optimization and efficiency	(Davenport and Harris, 2017)
Reduced costs and focus on metrics	(Fink, Yogev and Even, 2017)
Single source of truth, accurate data for decision making. Reduced time in compiling reports	(Luminiţa and Magdalena, 2012)
Better customer satisfaction, increased market share	(Singh and Samalia, 2014)
Increased ability to respond to changing environment, greater insights generated	(Sharma, Mithas and Kankanhalli, 2014)

Table 2.1-1 - Benefits of BI

Friedman (1970) opines that business' social responsibility is to its stakeholders; thus, it must constantly seek to increase its profits. Table 2.1-1 - Benefits of BI summarizes some of the benefits using BI. Several case studies report positive contributions of Business Intelligence's impact to profits: the giant logistic company UPS reported reducing 100 million miles using an analytical programme - Orion (on-road integrated optimisation and navigation) relating to half a billion US dollars saving a year in fuel costs (Davenport and Harris, 2017). Western Digital (reported operating costs halved); Netflix used analytics to gain insights of each viewer relating to profit increases in millions of US dollars; Continental Airlines reporting ROI of a thousand percent; CompUSA (ROI of $6 million in just the first phase) as well as a few others such as Google; Facebook and Amazon all use analytics to drive their businesses (Davenport and Harris, 2017, Watson, Wixom, Hoffer, Anderson-Lehman and Reynolds, 2006, Williams and Williams, 2010). BI's value proposition stretches across an organisation, and can provide insights about questions, about major cost operations, equipment reliability, customer segmentation, customer profitability, customer attrition, and supply chain optimisation (Verma et al., 2018).

Efficiency aligns to operational goals; which is to reduce costs and improve productivity and focuses on metrics, whilst effectiveness aligns with strategic goals - which focuses on profits, market share and competitiveness. BI offers both strategic and operations benefits. This only occurs if organisation is willing to be ambidextrous (Fink et al., 2017).

In the context of company time, BI is an expensive non-renewable; and thus, it is important to manage the time and utilise of resources to operate efficiently. BI offers a reduction of time to obtain reports and also offers a single source of the truth by data warehousing to overcome information ambiguity which leads to quicker decision making (Luminiţa and Magdalena, 2012). Using BI tools, large volumes of data from multiple sources can be analysed and presented in a visual intuitive layout that can easily depict problems and trends allowing quicker and more accurate problem solving.

Without a BI system, organisational administrators will need to collect real-time data across marketing and operations. The collected data will need to be able of answering very detailed questions to many audiences. There is also a challenge of increased time losses due to repetitive work and errors using incorrect assumptions. For example, information is not always compatible with the reports of other departments, and may mix jargon, thus, increases the amount of time to consolidate reports to give a holistic picture (Luminiţa and Magdalena, 2012).

Singh and Samalia (2014), reviewed several studies and listed major BI benefits such as improved decision making, better customer satisfaction, reduction in costs, increased revenue and increase in market share.

Organisations have a burden to provide stakeholder value which eventually results in financial gains. However, measuring BI value against the investment costs or how long it will take before BI are converted to financial gains remains a challenge (Elbashir et al., 2008, Jourdan et al., 2008).

If BI is considered as an investment, the most common assessment tool is cost benefit analysis which is to determine if the benefits outweigh the costs. Determining the TCO (total cost of ownership) must take into account the initial capital overlay as well as running costs, labour and so forth. However, the total benefit achieved is difficult to measure as there are many intangible benefits that arise. Although some lead to financial benefits, the time-lapse between is unpredictable, therefore, cost benefit analysis is often difficult to perform accurately. Other methods such as ROI, NPV, and payback period have the issue of determining the BI output in terms of cash-flow which are difficult to compute. Thus, it is understandable why few organisations have metrics implemented (Marin and Poulter, 2004) .

The two purposes of having BI measures are to justify the investment (BI credibility) and to better manage and improve the BI process of delivering BI products to satisfy user's information needs. Two aspects need to be considered. The first aspect is determining value to users. It is important to know which users (subjective measure – perceived usefulness) the organisation intends to satisfy. The second aspect to consider when assessing the value of BI is the result of the decision made based on the information provided by BI product as opposed to an intrinsic value (Kelly (1993) in (Lönnqvist and Pirttimäki, 2006)).

An early attempt at justifying business intelligence investment included the CI measurement model by Davison (2001) which related inputs (such as direct costs of BI project) to outputs (objective fulfilment and satisfaction) *via* a formula ROCII = (CI outputs – CI inputs) / CI inputs. It was useful in that it considered non-tangible outputs, and it could also be used to manage the BI process. However, it was criticised since it relies on qualitative data and thus unreliable.

The dynamic capabilities framework, suggests that asset combination in terms of resources provide the organisation with a unique capability, thus the importance on the organisation's search and select capability (Wade and Hulland, 2004). Managers usually need to collaborate across their departments and organisations to obtain the assets they require for the implementation; thus, governance is required. Operational agility is ability of organisation to respond to change, by having flexible organisational structure and processes. Questions as to which governance structures are more effective remain unanswered. There is also a portion of uncertainty that exists from organisations actions to actual outcomes, due to circumstances outside the control of the organisation (example, a VAT increase, or trade embargo). Analytics generates insights or options, which then decision makers must choose to act on or select among alternatives, they must then decide on the resource allocation and execution strategy and monitor the actions and changes to those actions (Sharma et al., 2014).

2.2. Information Quality

Data quality remains the most citied reason for BI implementation failure (Colas et al., 2014), and data cleansing costs in US alone was estimated at billions of dollars per year (Eckerson, 2002, Li and Joshi, 2012). Data entry problems such as misspelling, lack of input validation, incorrect formats and syntaxes reduce the quality of data (Eckerson, 2002).

High data quality does not always transcribe into high quality information quality due to the transformation processes in-between. However, high information quality requires a high level of data quality. Thus, managing data is paramount to ensure trust in the BI system as a whole (Wieder and Ossimitz, 2015, Wixom and Watson, 2001). It is argued that information quality is particularly more important in business intelligence systems than traditional systems since BI is used to make decisions (Wieder et al., 2012).

One of the first articles focused on having a better understanding of the problem of data quality in organisations was done by (Brodie, 1980) who proposed working definitions for the three distinct components that make up data quality: physical integrity - which is associated with the physical implementation to the desired model. Data reliability is a statistical measure that relies on a procedure of validation which checks values to defined schema. Lastly, semantic integrity is the consistency of the language to rules and requirement definitions. According to (Brodie, 1980), data quality is the extent to which the data fits the intended application. Brodie (1980) emphasised both the structure and behaviour components of data quality, and proposed a three-level model which extended from requirements gathering to design specification and finally to implementation.

Wang and Strong (1996) argued that previous literature to understand data quality (namely the intuitive, theoretical and empirical approaches) was subject to bias of the researchers' understanding of what dimensions contribute to quality, and quite often there were multiple dimensions. Brodie (1980) added that the literature failed to address the needs of the actual data consumer. In addition, Brodie (1980) warranted the study as it provided a framework to capture the essence from the consumer's point of view. It found that there were four categories of data quality which is represented below (Figure 2.2-1: Data Quality Framework Adapted (Wang and Strong, 1996)), and it has been widely used since.

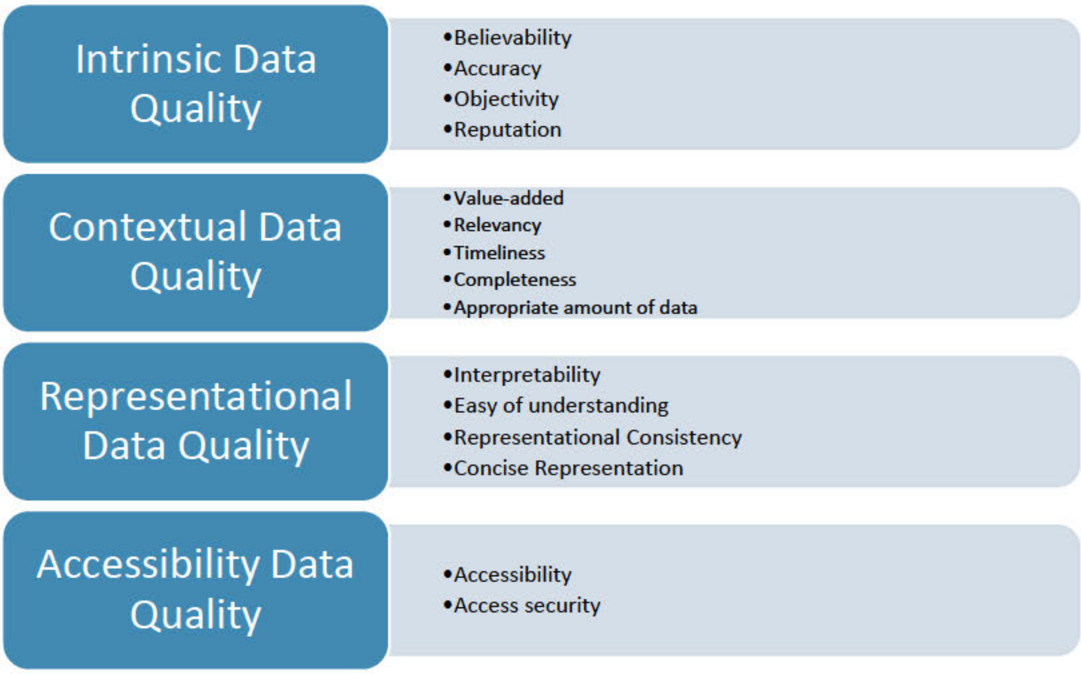


Figure 2.2-1: Data Quality Framework Adapted (Wang and Strong, 1996)

Intrinsic DQ refers to the degree of how the values presented in the data represent actual values. The contextual DQ represents how much of the data is relevant to the data user. Representational is how much the presentation of the data allows for clarity and how much it allows for a clear understanding. Accessibility is how available is the data to the data consumer. Information representation is important to convey to the decision maker. The context specific details must be included (Wieder and Ossimitz, 2015).

Data reliability is a statistical measure of data to exhibit structural properties (schema). Validation is the mechanism to check the data to ensure that the values abide by the schema properties. Integrity is a measure of correctness. Provability is the ability to verify data quality using systemic analysis (Brodie, 1980). Mechanisms must be in place to preserve the intended meaning of that data by the inputter.

Li and Joshi (2012) were some of the first researchers to investigate the cost/benefit analysis of data cleansing mechanisms. They found that there were several challenges to clean data in variety of formats into a single data warehouse. It was difficult to handle data redundancies across multiple sources, fix bad data due to typos and misspelling. Data is labelled as of bad quality if it fails to meet the organisation's quality standards. It is understood that IT is not responsible for the creation of data. However, it is often an expectation that IT will deliver high quality information products which support decision making, that is, the business expects IT to cleanse data. A prerequisite for a successful BI implementation is high data quality to which an understanding of the data is an antecedent. More often than not, the reason for failure is due to underestimating this understanding which leads to costly fixes in the post implementation phase - that is after the BI system is poorly perceived (Li and Joshi, 2012).

Ge and Helfert (2006) conducted a study using a group of post-graduate students to make decisions. A data clean-up improved the quality of decisions for the first round, but deteriorated as data grew stale. The study found that with bad data, the decisions were like gambling. The study suggested that a continuous improvement approach is required to maintenance and assessing the quality of data focusing on the dimensions such as accuracy, timeliness etc.

Wang (1998) argues that firms must put some effort to ensure data quality in as much as they work towards ensuring product quality. Organisations need to modify the manufacturing Total Quality Management methodology (TQM) to create the total data quality management (TDQM). This is currently still an issue in modern day information systems, and is better known as Master Data Management (MDM). An extension to the total data quality management methodology added weights to data because some data are more strategically important than others (Vaziri, Mohsenzadeh and Habibi, 2017). Data cleansing remains a key activity in ensuring good data quality which itself is the cornerstone of a successful BI implementation (Li and Joshi, 2012).

Information quality refers to the quality of the system output as perceived by the decision maker; often conceptualised as "fitness for use" (Wang and Strong, 1996:6). It is the information product (typically reporting) and includes measurements such as information accuracy, relevance, recentness, credibility, timeliness and importance (DeLone and McLean, 1992). Information assists in decision making by reducing uncertainties and removing assumptions. It can be used to predict consequences of a choice or action through a technique called 'simulation' (Wieder and Ossimitz, 2015).

A study on six large organisations by Otto (2015) found that organisations faced problems in managing the quality of their master data. It further maintained that the master data was a strategic asset which added to the competitive capability of the firm from the resource based view (Otto, 2015).

The study introduced a model of data quality, data lifecycle and data value. The quality of data included the attributes identified from (Wang and Strong, 1996) such as content, timeliness and cost. The lifecycle included data procurement, maintenance (changes to an address) and use for information. The data value divides the data into classes of strategic importance to less important. All six companies in the case studies experienced issues stemming from poor data due to the absence of a master data management strategy. There is a variety of techniques to monitor the quality of the data during the lifecycle. It must take into cognisance the time, scope and frequency of measurement. It was found that some large organisations took master data management seriously and had dedicated departments and data governance strategies in place to ensure data quality.

It is often assumed that high quality information leads to better decision making and ultimately better firm performance. However, it was found that the decision maker's understanding of the relationships between entities was paramount and recommended that the decision makers be included in the analytics process. It found that higher quality information reduced decisions if the decision maker did not understand the basic relationships between the variables whilst those that understood the relationships lead to better quality decisions. The study used the simulation approach, but it however corresponded with several other similar studies in terms of results (Raghunathan, 1999).

2.3. System Quality

A well designed system can yield many benefits and produce high quality data whilst a badly designed system can be costly and cause decision makers to lose trust in the system (Lin, 2010). (Wixom and Watson, 2001) conducted a study consisting of 111 organisations responding to a survey and made an analysis using PLS. The study concluded that system quality is significantly positively related to the perceived net benefits that the organisations enjoy. System quality refers to the quality of the actual system. It is mostly engineering-orientated and it has characteristics such as integration, response time, system accuracy, and flexibility (DeLone and McLean, 1992).

The updated IS model included a few more measures for the system quality construct including reliability, ease-of-use, functionality, portability and importance (Delone and McLean, 2003). Analytics is presumed to be the successor to decision support systems as it enables data from multiple sources and in different formats (structured and unstructured) to be integrated, processed, and it supports real-time insights based on the data (Wieder and Ossimitz, 2015).

(Nelson and Todd, 2005) conducted a study to better understand system quality in the context of data warehousing using a sample of 465 respondents across seven organisations. These scholars found that system quality is positively related to system satisfaction. See (Figure 2.3-1: Determinants of System Quality (Nelson and Todd, 2005)) show the five constructs to define system quality in their model were (i) reliability, (ii) flexibility, (iii) accessibility, (iv) response time; and (v) integration.

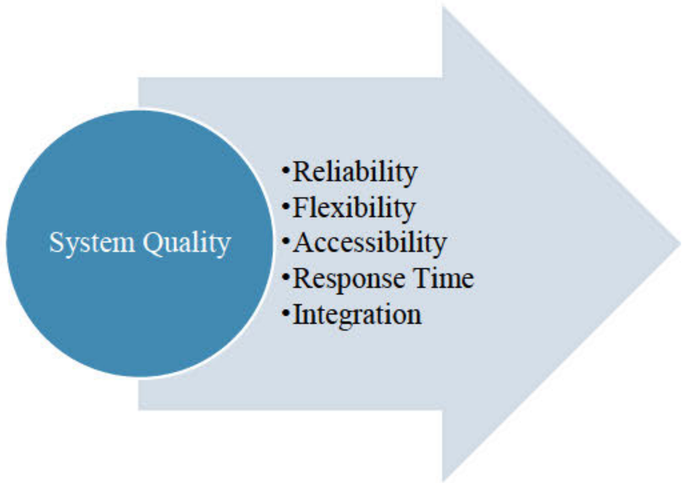


Figure 2.3-1: Determinants of System Quality (Nelson and Todd, 2005)

Reliability is a measure of how robust a system is. This relates to the absent of failures in the system as well as how quick it is able to recover from one a failure. A high-quality system must ensure that data quality in databases are free from constraints. Flexibility is the capability of the system to adapt to varying user needs and changing conditions such as supporting different types of data sources and providing multiple outputs of reports. Accessibility is the degree to which the system is available for use without much effort. Response time is the time that the system takes between a request to the response.

Integration is found to be a significant contributor to system quality. It was found that if source systems implemented a common standard or integration technology, it would improve the data quality and lead to implementation success (Wixom and Watson, 2001). Chee et al. (2009) stated that there is a lack of academic research on the integration between ERP and BI and the affects afterwards. This was especially lacking in developing countries. It found that integration yields the following benefits: (i) monitoring of cash flow in real-time, (ii) supporting better cooperation between departments, (iii) reducing the time required to generate regular reports, (iv) improving profitability, and (v) improving accounts payable and customer relationship management.

2.4. Service Quality – BI Team

Service quality is focused on the efforts of the IT team in providing the information product (information provider) and supporting end users (service provider) (Delone and McLean, 2003, Karlinsky-Shichor and Zviran, 2016). In information systems adoption context there is an argument that service quality is not significant to perceived benefits (Venkatesh, Morris, Davis and Davis, 2003). However, in the area of knowledge management systems, it was found that service quality was a significant influencing factor (Karlinsky-Shichor and Zviran, 2016).

There is a research gap on the management of BI resources (essentially BI management) beyond implementation and how that management affects the quality of decision making in the organisation (Wieder and Ossimitz, 2015). Early studies on critical success factors identified BI management capabilities as a pre-requisite to ensure success. It must manage the holistic process from data creation through transformation to BI products and use (Yeoh and Koronios, 2010, Yeoh and Popovič, 2016).

There is no accepted scale for measuring BI management quality (Wieder and Ossimitz (2015). However, measures such as BI resources skill, BI development methodology standardisation and percentage of BI projects within time and budget of planned are some of the scales used for measuring BI. BI management must ensure that they produce BI outputs aligned to business. They must support decisions and solve problems by providing relevant information. High quality BI management and skills ensure better quality of decision making by ensuring that the quality of the information is fit for purpose. It also ensures that data quality is adequate for organisational decisions needed (Wieder and Ossimitz, 2015).

A quantitative survey administrated to 500 Australian public companies regarding questions on BI management, data and information quality, BI scope and decision making quality revealed that BI management positively affected the quality of decision making (Wieder and Ossimitz, 2015).

Whilst decision making involves choosing between desired future outcomes based on the information supplied, the task of supplying the information must anticipate the decision before hand and accommodate mechanisms to collect, store, analyse and present the data in such a way that it is clear to the decision maker which path to choose. This elaborate task is the responsibility of BI management (Wieder and Ossimitz, 2015).

Analysts are experts with analytical tools and statistical knowledge whilst business decision makers understand the domain and the existing gaps. Thus, explanations given by analysts must not be too technical for the business person to understand otherwise they will neglect the advice and rely on intuition (Kowalczyk and Buxmann, 2015). Often, during requirements gathering, the right questions are not asked, and this leads to changes while the development of the BI model and analysts must adjust accordingly to changing needs. This is referred to as the ‘ambidextrous problem’ that analysts and data scientists face with conflicting goals and comprising to find a balance.

Whilst basic analytic products such as predefined reports and simple descriptive statistics and dashboards are easy to comprehend by most business decision makers, advanced analytics products such as time series analysis, neutral nets, simulation and optimisation results are intimidating to business decision makers. Thus, they require strong collaboration with analysts in the interruption and advise on the choice of action based on the product. The gap between the analysts and business decision makers is heighted by the business expert’s lack of advanced analytics knowledge and is further increased by the analyst’s lack of business knowledge. The heuristic system model (HSM) distinguishes between two types of information processing mechanisms: (i) heuristic processing uses a set of simple inferential rules to make decisions and (ii) systematic processing which uses analytics methods and extensive use of information (Kowalczyk and Gerlach, 2015).

The role of the analysts in influencing the decisions is paramount when using complex analytics processing methods. There are very little studies focusing on the analyst’s role as mediating. A study using data from 136 decisions using BI revealed that high levels analytics reduced the quality of heuristic making decisions whilst with collaboration of analysts, it significantly increased the quality of systematic making decisions (Kowalczyk and Gerlach, 2015). The practical advice from the study is that the culture and context determine how valuable and advanced analytics will be. If there is an information anarchy approach to information and when managers rely on heuristic methods and intuition, then advanced analytics might do more harm, and the suggestion is to rather use basic analytics under the culture changes. It also found that the more trustworthiness the analyst’s credibility is, the more influence on the undertaking of the advice.

Data scientists must help organisations to provide (i) retrospective historical view *via* products such as reports and dashboards that support decision making, (ii) predictive view that analysis historical data and presents a view of the future and (iii) prescriptive view that analysis a set of actions and recommends the most optimal course of action (Power, 2016).

Data scientist is viewed as an evolved analyst role with more focus on business and methodology to ensure that the tasks with the highest business value are done first. Data analysts are also experts who are able to analyse more complex data to provide a more prescriptive result than supporting decision making. Power (2016) provides a list of the 22 skills that the data scientist should possess.

Adoption theories that report on managerial intensions to adopt the analytics system based on innovativeness of manager might be bias in that they do not take the organisational viewpoint but rather the individual manager intension. A study using 62 managers found that managerial involvement in the adoption process had a significant positive relationship to adoption intension (Wang, 2014).

2.5. BI Competency

The resource based view is that a firm has superior performance due to a specific arrangement of rare resources or assets, that provide the organisation with unique capabilities that make it competitive (Wade and Hulland, 2004). Assets transcribe to anything a firm can use for its product or service offering whereas capabilities are the repeatable actions that encompass the use of assets for its service or product offering to the market (Sanchez, 1996). Thus, BI assets are the basic building blocks for BI capabilities (Fink et al., 2017).

The range of possible tools, the sophistication of analysis techniques and visualisations mediums that are available to an organisation are referred to as BI scope. These are often a mix of software and analytics capabilities within the firm to offer a BI product. It was found that BI scope was positively related to the decision-making quality. Furthermore, effective BI management improved BI scope (Wieder and Ossimitz, 2015). Tippins and Sohi (2003) conducted an investigation on how IT competency influenced organisational learning, and they found positive significant relationships between IT competency and firm performance. It concluded that IT competency influenced the success of IT projects, and thus firm performance.

Ramakrishnan, Khuntia, Kathuria and Saldanha (2016) developed a survey instrument to test how BI capabilities influenced BI organisational effectiveness. BI capabilities were defined as the ability to mobilise and deploy BI functionalities in combination with other resources and capabilities. It comprised three specific capabilities (i) BI innovation infrastructure capability, (ii) BI process capability and (iii) BI integration capability. BI process capability is the measure of how much BI is able to penetrate or be part of the normal business process. It must have a customer viewpoint in order to accommodate customer queries and requirements, and should also ensure customer retention. This means that BI must provide valuable customer insights which is used to grow the existing client base. It should also ensure that the organisation is able to absorb customer information into the organisation.

Past technologies that created value for organizations have done so by re-organising resources and changing the organizational structure, these were technologies such as knowledge management systems, executive information systems and enterprise resource systems. Current research into BI implies that decision makers armed with better analytic tools and high-quality data will make better decisions while continuing to function as before, more research into the resource allocation and structure changes are required (Sharma et al., 2014).

The contingency theory states that there is no single best way for all situations, and that the context is important for the solution. Thus, there might not be a single arrangement of BI assets and resources that exist as industry best practice, but it will need to be adapted according to each organisation context. The extent to which organisational resources work well together with the assets will differ the distinguish the company from its competitors (Fink et al., 2017).

BI value when viewed under the lens of learning and innovation means that the ability of the organisation to incorporate into their processes inferences from data integration and analysis, and extract this knowledge to focus on innovation and generate organisational intelligence (Fink et al., 2017).

Human BI resource will have technical skills, domain knowledge and behavioural skills (such as offering advice to non-technical decision makers without technical jargon in a manner that is easy to understand). BI assets are comprised of hardware and software (such as reports, dashboards, predictive and prescriptive outputs).

BI evolved from decision support systems which are mostly used for strategic decision support. However, with advances in infrastructure and support of multiple sources, BI was shown to support operational decision making. Thus, several studies report on strategic and operational value of BI separately.

March (1991) in his study introduced a framework which explained how organisations learn and innovate by using two styles, exploration of new competencies and exploitation of existing competencies. Exploration was concerned with new opportunities using discovery, risk taking and flexibility as characteristics whilst exploitation was focused on refining existing competencies defined by characteristics such as cost reduction, efficiencies, selection and execution ((March, 1991) in (Fink et al., 2017)).

Fink et al. (2017) divided BI capability into strategic - which aligned with the exploration and operational - aligned with exploitation under the lens of organisational learning and innovation style. It argued that organisations must become ambidextrous and pursue both objectives by having both capabilities simultaneously. Strategic BI capability that provides information about new opportunities or threats and orientate towards risk-taking and discovery yield new innovative products and services. Operational BI capability provides information that is used to improve daily operations resulting in streamlining activities. Innovation on existing products and services occur incrementally. Operational BI capability yields quicker and immediate value as gains to efficiency occur whilst strategic BI capability yields longer more risky value.

2.6. Decision Making Quality

Human brains consist of two conflicting parts of the brain, the “old brain system - affective” developed millions of years ago featuring instant decision-making mechanisms allowing us to survive clear present danger such as predator threats and the “prefrontal cortex system – deliberative” developed approximately 150,000 years ago featuring deliberative decision-making mechanisms that allows us to make complex business decisions such as mergers and acquisitions. These two brain systems are often in conflict (Abbas and Howard, 2015).

A decision is defined as the irreversible outcome of committing resources (human resources, capital, material, time) to a choice between several alternatives (Abbas and Howard, 2015: 8). Good decisions can lead to competitive advantages whilst poor decisions can lead to bankruptcy. Recently, organisations are starting to realise the importance of information quality (Ge and Helfert, 2006). It is well established that in practice, most decision making in organisations are done in a non-rational way. This is referred to as “gut feel” decision making which uses the affective system of the brain. This is also known as the bounded rationality constraints problem whereby parameters such as time or knowledge are limited (Riabacke, Larsson and Danielson, 2014).

Whilst a good decision is that which produces a desired outcome, Abbas and Howard (2015) argue that the six elements of the decision need to be understood (see Figure 2.6-1: Decision quality - qualitative model (Abbas and Howard, 2015)), these are: (i) the decision maker (ii) the frame which is the viewpoint (iii) alternatives from which to choose (iv) preferences (v) information and (vi) decision logic which is the process employed to derive the action.

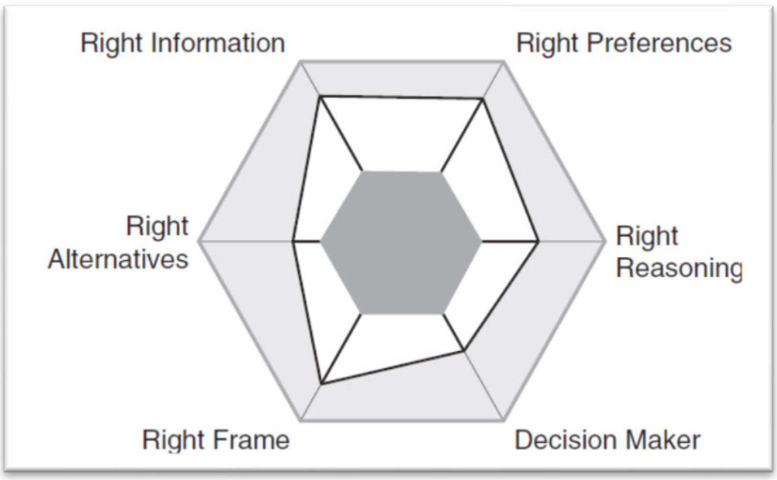


Figure 2.6-1: Decision quality - qualitative model (Abbas and Howard, 2015)

It follows that the qualitative model of decision quality contains these six elements: (i) decision maker (ii) right frame (iii) right alternatives (iv) right information (v) right preferences (vi) right reasoning.

Whilst Newtonian science viewed phenomena as systematic, linear and predictable, chaotic theory views phenomena as complex, non-linear and unpredictable. It must be noted that chaotic theory was not a replacement, but an alternative when the context demands (Goldoff, 2000). Two areas of decision-making that are not intuitive and require a methodical process and involve higher thinking are (i) risk assessment and (ii) strategic management.

Strategic management involves goal setting and planning, execution and monitoring. Strategic decision making requires decision makers to choose among various alternative strategies by evaluating the value. It follows the normal problem-solving process.

Risk analysis is a process which involves doing research and collecting data, then performing a risk assessment and risk management. Risk is defined as the probability of an event occurring usually harmful (injury, damage, loss). It is often expressed as the equation.

$$Risk = probability\ of\ frequency\ x\ Severity$$

Risk assessment requires applying past knowledge to predict the likely occurrence in the future. It is a quantitative task, and requires rational thinking and follows a structured process. Risk prioritisation also follows a structured process whereby potential risks are evaluated in terms of a risk score to determine which priorities to divert time, budget and resources to. Risk management and risk communication try to eliminate the risk, reduce the outcome and supply information of the hazard for prevention.

Chaos theory involves looking at an unordered, unpredictable and irrational system from a higher dimension to better understand the phenomenon. It acknowledges the butterfly effect, and acknowledges that systems although similar, differ based on context. Kiel’s third principle of chaos implies that an unusual event has the potential to change an entire system, and unwillingness of managers to adapt and rather stick to status quo leaves the whole organisation suffering its consequences (Goldoff, 2000).

Organisational scientific enquiry or rational thinking is defined as the actions of firms to seek truth, exercising higher order reasoning and take appropriate actions to pursue economic goals (Power, 2016).

Whilst there are numerous studies on decision theory, there are little studies focusing on decision-making within an organisational setting. Normative decision-making theory (NDMT) helps decision makers to make better decisions by prescribing a decision-making process and by guiding how to make the decisions. See (Figure 2.6-2: Normative decision-making theory process), this process starts with problem recognition, and end in choosing the most appropriate strategy to achieve the outcome. The theory tries to consider all aspects of the issue by practising due diligence. It further purports that the quality of decisions depends on the outcome.

Figure 2.6-2: Normative decision-making theory process

Akdere (2011) reviewed literature on the study of decision-making and found eight common techniques used in organisational decision-making process. This study used 71 students to pretend as organisational members then ranked different decision-making processes. Three variables used were the quality of the decision making, systematic planning and decision-making performance. The results showed that brainstorming yielded the best quality decision making process while affinity diagramming contributed the most to systematic decision-making process. Flow-charting was found to have the highest score in decision making performance. Lastly, the consultative decision-making process contributed the most to group learning process (Akdere, 2011). The study ignored the ethical limitations, and therefore might not be valid due to an inaccurate sample selection (using students to pretend as organisational members). The study itself called for further research in this area.

2.7. BI impact on decision making and firm performance

Trieu (2017) reviewed empirical studies seeking BI organisational value and found that there was a general lack of investigation in this area. The review of literature suggested that future studies should be multi-level and should focus across the lifecycle from BI investment, through to BI impact and improved organisational performance.

Although cost benefit analysis is used by managers to acquire BI systems, it is the employees or users of the system that determine how successful the system will be. Several authors agree that this is achieved through adoption and diffusion throughout the organisation (Davis, 1989, DeLone and McLean, 1992, Devaraj and Kohli, 2003, Rahman, 2016, Verma et al., 2018).

Figure 2.7-1 - Diffusion stages of BI in the organisation

Côrte-Real et al. (2014) did a literature review study of several articles over the last decade relating to business intelligence and classified them according to the stages that it is diffused into the organisation see (Figure 2.7-1 - Diffusion stages of BI in the organisation). The study found that 23% of articles revered focus on adoption theories such as technology acceptance model and technology organisation environment. The bulk of studies, 33% concentrated on implementation, as it is complex and takes a lot of time and resources, therefore so many studies focused on critical success factors. A common theme that emerged, was that change management and the softer issues were more time consuming and a hindrance, than technology problems. The most popular models in determining the use to its impact of use, was the DeLone and McLean model and the diffusion of innovation (DOI) model. Another common theme was that studies reviewed showed that higher levels of system usage lead to better firm performance, this was explained as, firms receive benefits of BI through insights which make them more competitive (Côrte-Real et al., 2014).

The most popular adoption model used in information systems literature is the technology acceptance model (TAM), see (Figure 2.7-2: Technology Acceptance Model (TAM) - adapted from (Davis, 1989)). It was based on reasoned action (TRA) which explains that behaviours are based on behavioural intention. It assumes that people act rational (Ajzen and Fishbein, 1980). The TAM provides an explanation that people find the technology useful for their work, given by a measure perceived usefulness (PU), and secondly because it is easy to use with a measure of perceived ease of user (PEOU). It also hypothesised that PEOU will have a direct effect on PU (Davis, 1989).

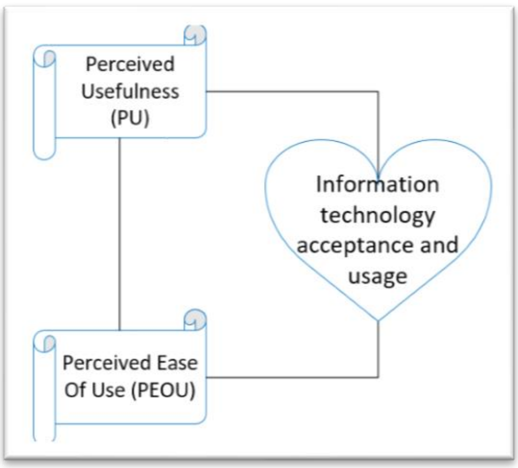


Figure 2.7-2: Technology Acceptance Model (TAM) - adapted from (Davis, 1989)

Perceived usefulness is the degree to which the use of the information system will enhance job performance while perceived ease of use is the degree to which the system will be intuitive, free of excessive mental and physical effort (Davis, 1989).

A recent extension to the technology acceptance model for big data adoption included vendor support, security and privacy and workforce expertise which are antecedent to attitude towards usage (Rahman, 2016). However, it failed to show how these factors are addressed in emerging economies like South Africa and India (Verma et al., 2018).

A study conducted in Malaysia with 427 participants modified the TAM to create ETAM (e-Service technology acceptance model). It included satisfaction and security as antecedents to intention to use and found that quality, security and satisfaction were major influences to usage (Taherdoost, 2018).

A 'system belief' in the context of systems theory is the degree to which a user perceives benefits of a system. A recent development of the TAM model included the belief dimension as well as the perceived quality variables (*system quality and information quality*). It then tested this modified TAM model *via* a survey among 150 BI users and found a positive strong relationship between perceived information quality and BI system belief. It also found positive relations between BI system belief and perceived ease of use and perceived usefulness (Liao and Tsou, 2009).

Information transparency refers generally to openness of data or free flow of information. Internal information transparency is the degree to which an employee is able to acquire the necessary information to make business decisions. External information transparency is the degree to which information to external stakeholders is made available. A study which modified the TAM to include information transparency found that information transparency had significant and direct effects on perceived ease of use and usefulness. It was tested among 106 ERP users (Al-Jabri and Roztocki, 2015).

In addition to (Liao and Tsou, 2009) model of the two independent constructs of system quality and information quality, a belief in BI system construct was added to test big data analytics adoption using a survey of 150 users. It confirmed the original TAM relationships but with the addition of the beliefs. It found that the strongest positive significant relationship was between information quality and belief in the BI system (Verma et al., 2018).

DeLone and McLean (1992) reviewed existing literature which included 180 articles and proposed a framework consisting of six dimensions which contribute to information system's success. They also extended on Mason's model to include the six dimensions throughout the transfer stages.

Information use in the literal sense measures the use of the information product which is the frequency of report viewing. However, later studies introduced different levels of use such as general use (routinely as part of business process) or specific use in complex decision making as well as actual or perceived use (DeLone and McLean, 1992). Several measurements include frequency of use, voluntariness of use and extent of use.

User satisfaction relates to the perception of overall system satisfaction from user's point of view. It is evaluated on the pleasant and unpleasant continuum (Karlinsky-Shichor and Zviran, 2016). It includes several measures such as enjoyment, information satisfaction and decision satisfaction (Delone and McLean, 2003).

Individual impact is more of a slippery concept relating to how the system assisted the user to make a decision. The most used measures include value in decision making, confidence in decision, number of alternatives considered, time to decision, monetary value of information and insights from analysis of the data (learning value of data). Organisational impact encompasses all the overall individual impacts and includes measures such as profit, cost reduction, market share, overall effectiveness and overall efficiencies.

In a ten-year update, the framework was reviewed and several works that empirically tested multi-dimension constructs of IS success were presented. The study also reviewed the various criticisms whereby the model served to be confusing because it combined both a casual and process framework into one. The authors reviewed this criticism and acknowledged that the model was confusing. However, researchers disapproved the idea of splitting the model into two. The researchers argued that the model should rather be viewed as an extension to the model to include service quality modified from the 22-measure SERQUAL instrument. It also grouped several impact measures into "net benefits" category (Delone and McLean, 2003).

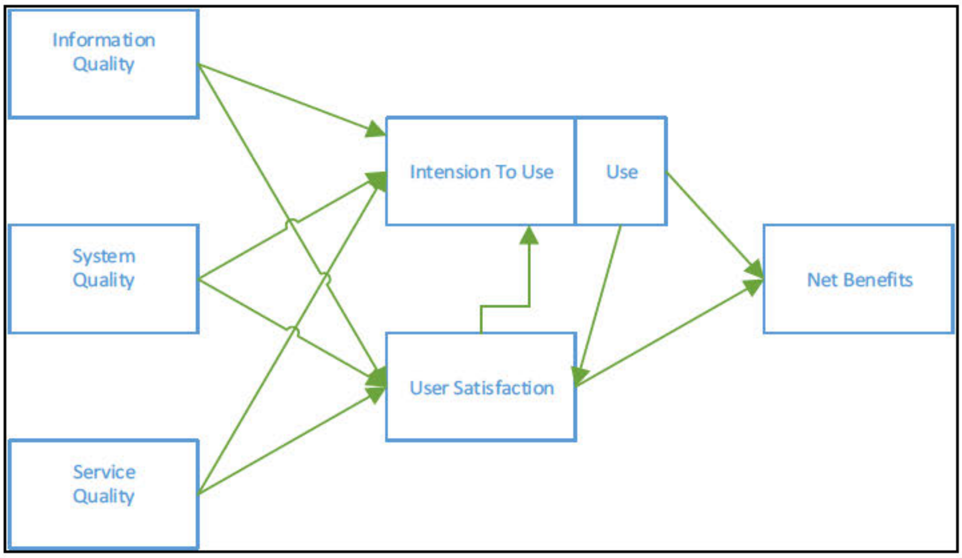


Figure 2.7-3 Updated D&M IS Success Model – adapted (Delone and McLean, 2003)

It was advised that the success of IS be treated as a multidimensional construct. Thus, researchers must chose several appropriate measures based on the context under study (Delone and McLean, 2003).

Wixom and Watson (2001) proposed three levels of success that must be deployed for the warehousing to be successful: organisational implementation success (involves widespread adoption across the organisation and integration into business processes, overcoming resistance to change from users); project implementation success (ability coordinate roles and tasks to deliver within budget, time and meet end user information requirements); and technical implementation success (overcome technical difficulties that arise from reconciling data from different source systems

Committed Management Support and Sponsorship is one of the most identified crucial factors for IS success initiative. Several studies found that users are more likely to accept a system if it conforms to the expectations of management and receives proper recognition (Wixom and Watson, 2001, Yeoh, Koronios and Gao, 2008). Management support is crucial in breaking down silos that exist across the organisation and helps ensure smooth training.

Resources include people, time and money: sponsorship for BI initiatives differs from a once-off traditional IS budget since BI requires a continuous flow of budget that is adaptive. Therefore, it is important to have strong commitment in terms of a budget (Yeoh et al., 2008).

During the earlier stages of information gathering, analysts rely heavily on business and end-user participation to provide input into user requirements and assist on unclear requirements. Researchers argue that goals must be clearly understood and will lead to the system being more likely accepted. Active user participation during testing is also required and training of end-users (Yeoh et al., 2008). Wixom and Watson (2001) found that if source systems implemented a common standard or integration technology, it will improve the data quality and lead to implementation success.

Several studies found that data quality and system quality had both significant positive relationships with perceived net benefits (Wixom and Watson, 2001). Implementing a BI system organisation wide is a massive, and complex task involving several stakeholders and mostly is an ongoing initiative unlike typical IS implementations. However, the literature on BI Practitioners is limited (Yeoh et al., 2008).

Yeoh et al. (2008) addressed the gap of critical success implementation factors by using the three rounds of the delphi method among a group of 15 BI experts and found seven contextual factors and elements were important for implementation success. The study was not empirically tested and called for several case studies to test model.

It is important to have a clear business vision and a well-established case to align the BI project to the overall organisation strategic goals. It will play a driving role during change management, and measurements for return on investment should be developed at this stage (Yeoh et al., 2008). The BI must be shown to solve real organisation problems and a solid business case is required.

Several success models propose strict project management approaches. However, Yeoh et al. (2008) recognise that BI is an ongoing project, and recognises the benefits of incremental delivery through agile BI. It also provides guidelines that adequate scoping could help. However, small changes favoured over large changes.

A business centric championship is critical. The champion needs business acumen using strategic view and is not necessarily familiar with technical tools (Yeoh et al., 2008). A champion is an identified person who is part of the project implementation team and is often from the organisational side. This person displays transformational leadership behaviour to drive and support the BI adoption process and overcome any resistance that may arise by fostering good relations between themselves and the users and guide them to a common understanding that the BI system will make their jobs easier and help achieve the organisations goals (Wixom and Watson, 2001). However, for the warehousing success study, it was not found as a critical function for organisational implementation success.

Having a balanced project team composition is also identified as CSFs for BI success. This is a mix of IT teams with technical and business people (Wixom and Watson, 2001, Yeoh et al., 2008). A strategic and extensible technical framework: a technical robust, scalable framework abiding to industry benchmarks should be developed and used. Suppliers must ensure that source systems can integrate into the framework otherwise costly adapters must be developed.

Having a sustainable data quality and governance framework is paramount to ensure the quality of data; often issues with source systems, are not discovered until presented in BI report. Data governance must seek to improve the quality in back-end source systems otherwise this ripple effect will lead to bad decisions (Yeoh et al., 2008). The governance is the most underestimated part of BI systems, people must be responsible for the data input. There must be a governing committee and data must have representational consistency (Yeoh et al., 2008). Procedures and policies must be put in place to ensure compliance with regulators. Often, there is a need for consistent terminology across silos. A development and maintenance of a metadata model is important.

A study of adopting knowledge management systems using 100 respondents in Israel proposed a model for predicting perceived benefits and user satisfaction used four independent variables namely; system quality, knowledge quality, user IS competence and organisational attitude. It found that there was no significant relationship between perceived benefits and user satisfaction. It also found no significant relationship between user IS competence and perceived benefits and no relationship between organisational attitude and user satisfaction as well as perceived benefits (Karlinsky-Shichor and Zviran, 2016).

Gatian (1994), did a study that involved 39 organisations and found a strong relationship between decision quality and user satisfaction.

Nelson and Todd (2005), found that there is not a significant relationship between IQ and information satisfaction, they attributed it to users been unable to separate the output from the BI asset from the system itself that is they have an over-reliance on the system itself.

See (Figure 2.7-4: BI Satisfaction Model (Dooley et al., 2018)), is a model extending DeLone and McLean model, however this concept was split into information satisfaction and system satisfaction (Dooley et al., 2018).

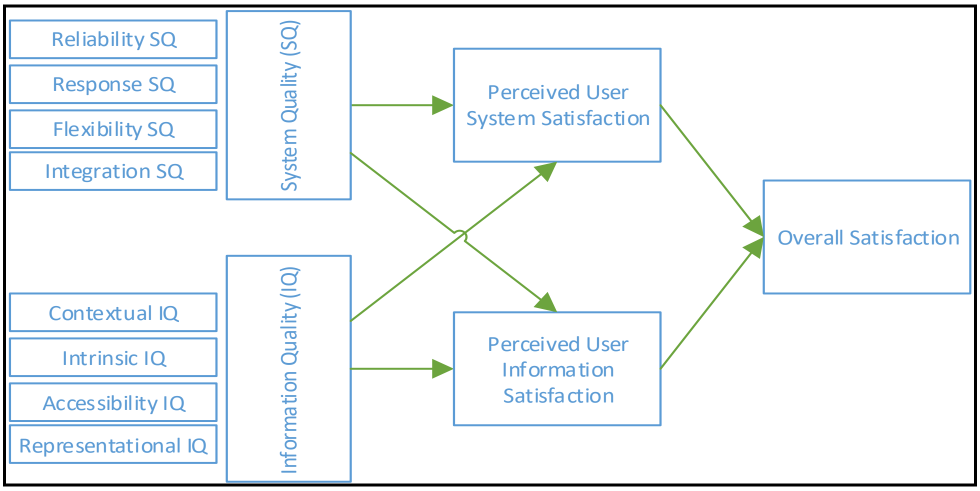


Figure 2.7-4: BI Satisfaction Model (Dooley et al., 2018)

Integration flexibility system quality compromised of extendibility, expandability, configurability and adaptability, all driven through an intuitive user interface. Results found that integration flexibility system quality explained largest variance in system quality satisfaction (Dooley et al., 2018). Reliability system quality explained the remaining variance, it is comprised of system dependability, recoverability and low-downtime. Results found that representational information quality explained largest variance, traceability and verifiability, ease of access and searchable information explained the rest of the variance (Dooley et al., 2018).

Results showed system quality had a positive significant impact on perceived user system satisfaction and showed that information quality has a positive significant impact on perceived information satisfaction (Dooley et al., 2018). Integration flexibility system quality is integration ability to support various formats, from multiple sources, for varying department needs, it is the extent to which it is compatible with other systems. Flexibility system quality is the degree to which BI system supports adhoc queries in various formats. Representational information quality is the choice of presentation and format, it had the most significant influence, it was noted that traceability such as audit fields on whom was responsible and verifiability were highlighted as important. Intrinsic information quality, was also found to be important to perceived information quality satisfaction (Dooley et al., 2018).

The IS success model stems from the communication theory whereby information must transfer in stages from the point of creation (production) to its final consumption (receipt) which is often where a decision is made based on it (Mason, 1978). See (Figure 2.7-5 Categories of information system success adapted from (Mason, 1978, DeLone and McLean, 1992)) which shows that for the production phase, system quality is vital whilst at the product stage information quality is paramount for use and decision-making, this model also depicts how information flows to affect organisational performance.

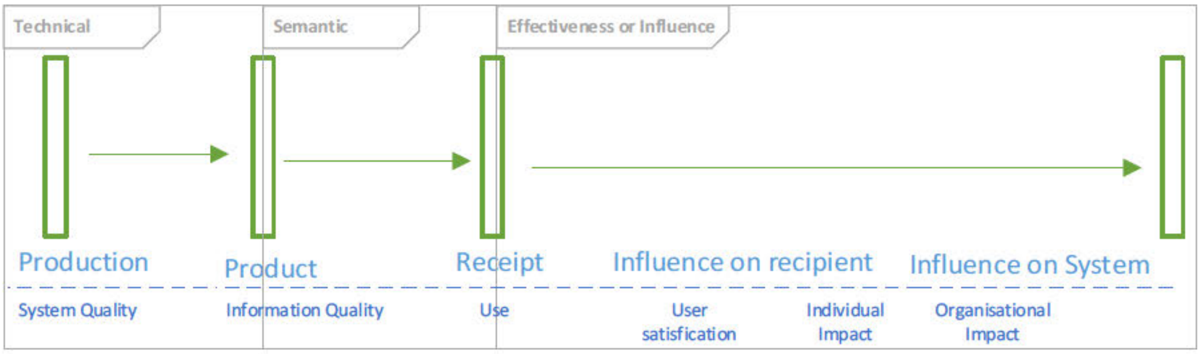


Figure 2.7-5 Categories of information system success adapted from (Mason, 1978, DeLone and McLean, 1992)

There is a lack of research showing how business intelligence is used to improve the quality of decision making in organisations (Cao et al., 2015, Janssen et al., 2017). Even the literature focusing on BI success overlooked decision making quality. Thus, there is little empirical research (Visinescu, C. Jones and Sidorova, 2015).

Recent studies show that only a quarter of companies report that business intelligence improved organisational decision making performance (Phillipps and Davenport, 2013, Colas et al., 2014). Several reasons given include challenges such as poor data quality, lack of analytical skills and organisational factors. Ghasemaghaei, Ebrahimi and Hassanein (2018) argue that firm resources play a critical role in ensuring that BI leads to improved organisational decision making.

Sharma et al. (2014) introduced a model to explain the process of how insights can be transformed into better decision-making, and ultimately business value, the model follows the RBV theory particularly focusing on the arrangement of resources and structure to create unique dynamic capabilities (see Figure 2.7-6: Data insight decision value flow – adapted from (Sharma et al., 2014).

Figure 2.7-6: Data insight decision value flow – adapted from (Sharma et al., 2014)

The first stage is data to insight, it must be noted that insight is not merely the results after analysis of the BI system, rather insights emerge out of engagement between analysts and decision-makers, these engagements that take place would require a change to the organisational structure to support and facilitate this engagement between analysts and business managers (Kowalczyk and Gerlach, 2015). Pre-existing frames of references and sensing allow managers to see patterns and relationships and generate insights, however these operate in a sub conscious manner and not easily translated into analytics (Sharma et al., 2014). Machine learning is as advanced analytics to understand patterns and relationships of the data, and allow the algorithm to take decisions based on this insight. There was much success in the use of artificial intelligence in automated decision making, such as credit card fraud detection and automated trading of stocks, Jarrahi (2018) explained how artificial intelligence could argument human cognition and not replace it, rather create a symbiosis to create even better insights.

Davenport and Harris (2007) suggested a business intelligence competency centre which is a central unit that will be able to collaborate with other business units, however (Sharma et al., 2014) shows that it is difficult for the central unit to convert their insights into value because of competitive actions by business units.

The second stage is converting insights to decisions. There is not usually a one-to-one mapping from insight into decision making, as the process involves several steps including selection among alternatives, resource allocation and execution. It is argued that collaboration about the options from analysis is where decision makers act as a value creation engine, by engaging in debate to convert the various insights into the best decision for the desired goal and hence the competitive advantage is dawned (Frisk, Lindgren and Mathiassen, 2014). Insights to decision is not obvious and easily automated, consider the case study whereby UPS saved fuel and time by minimising on left turns by using alternative routes, however the decision from the insight was to outsource those routes (Davenport and Harris, 2017). This was not an obvious decision, but yielded maximum returns for UPS, thus an example of how insights and collaboration between decision makers lead to a successful implementation for the company and yield reduced costs (Sharma et al., 2014). A challenge is the shortage of trained analytical personnel facilitating the conversation of insights into value, insights require deep and intuitive understanding of the phenomena (Power, 2016, Sharma et al., 2014).

The last stage of the model is decision to value. Good decisions still require good execution to yield a successful implementation, studies show that decision acceptance by subordinate's influences their motivation and thus leads to better implementation (Sharma et al., 2014). Managers face uncertainty with the availability of resources, and or the skills required.

Measuring success using various indicators such as stock returns are not direct measures, since there is mediating variables that are difficult to measure, such as customer satisfaction (Lönnqvist and Pirttimäki, 2006). Studies have shown that a data-driven organisation do achieve better performance by reducing costs, increased sales, optimizing risks, and leveraging on new opportunities (Davenport and Harris, 2017).

A case study in the Dutch revenue collection organisation found that several factors influenced decision making quality such as analytical tools and knowledge (analytical capabilities), process integration and standardisation which results in lower efforts, standardisation, and staff with specialist skills. Experience of decision makers lead to faster decisions, communication and knowledge exchange (good relational governance) and collaboration between analysts and decision makers (Janssen et al., 2017).

Another study by (Ghasemaghaei et al., 2018) surveyed 151 IT managers and data analysts in order to understand how data analytics competency affected decision making performance in organisations. The study (see Figure 2.7-7: BI impact on decision making performance – adapted (Ghasemaghaei et al., 2018)) found that all factors positively affected the quality of decision making in organisations. However, it was found that huge amounts of data were significant and imperative for decision efficiency (Ghasemaghaei et al., 2018).

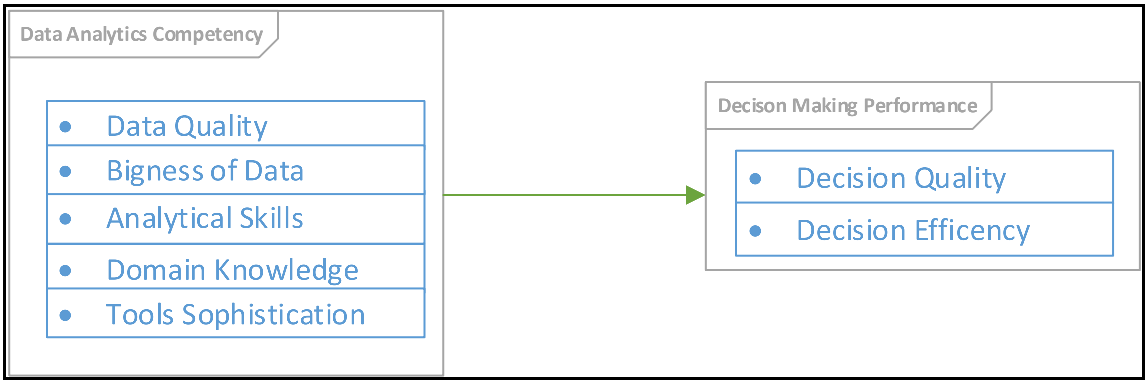


Figure 2.7-7: BI impact on decision making performance – adapted (Ghasemaghaei et al., 2018)

Employee domain knowledge is defined as the deep understanding about the internal procedures and processes of the business functions and their impacts. Analytical skills is the capability of being able to analyse and interpret data to gain insights (Ghasemaghaei et al., 2018).

Tools sophistication is the maturity and complexity of the analysis tools. These range from simple reporting to more sophisticated tools such as predictive analysis which provide forecasts and future insights recommending a course of action. It was found that the more sophisticated the tools in use the better the decision making performance (Ghasemaghaei et al., 2018).

A mixed methods study was conducted in a Swedish firm in order to understand the impact of BI on decision making. The study found several problems which the researchers believed were as a result of treating the BI system as another information system. Results showed that employees felt that their decision processes were not well aligned with the organisation goals. The BI system was aligned to departmental but not organisational goals. BI reports remained voluntary and there was confusion as to the value it added since there were no measurements available. Respondents felt it only showed partial information and was not useful. It was also noted that upper management involvement was missing. Decision making using BI reports relied on experience of the user and ability to create insights. It was not used by employees on strategic and tactical levels. These researchers believed that the main emphasis was on getting the BI system rolled out while no much effort was placed on understanding the nature of a BI system and its readiness (Riabacke et al., 2014).

Problem space complexity is the variety of factors in the context of the problem such as time available, tools available, knowledge and information accessible. It follows that the higher the complexity of a decision, the more effort and information is needed, therefore the higher the perceived quality of the decision (Visinescu et al., 2017).

Visinescu et al. (2017) conducted a study investigating the perceptions of the quality of decisions made using BI, and proposed a model of factors influencing the quality: (i) level of BI use (ii) problem space complexity and (iii) information quality. It collected survey data from 61 BI users across several industries in US and found that these factors had a positive relationship to perceived decision quality using BI. The study found one unexpected outcome which was under the conditions when the information quality was low. That is, a level of higher BI usage led to lower quality of decisions. However, as the quality of information increased, the quality of decision making increased as well. It was thus suggested that there is a tipping point of information quality at which positive outcomes for BI usage will be realised.

Adrian, Abdullah, Atan and Jusoh (2018) proposed a model consisting of three dimensions consisting of organisational, people and technology to have in place during implementation to ensure effective decision making.

The people dimension focuses on collaboration efforts, it is made up of (i) analytics skills which is ability of the personnel to successfully understand and interpret the analysis outputs and results (ii) organisational relationship which is the collaboration between analysts and decision makers and (iii) analytics culture which is the belief and practice of basing decision based on evidence from data. The technology dimension focuses on execution and consists of (i) infrastructure which incorporates the systems and applications used for analytics (ii) information processing which is the capability of the platform to process the data into meaningful insights (iii) data governance which includes policy formulation, processes and management of data (iv) data quality management which involves managing the transformation process to ensure high quality information. The organisational dimension focuses on strategy and consists of (i) strategic alignment to ensure that the analytics goals align with the larger organisational goals (ii) managerial commitment which requires top management support and financial commitment and (iii) resource management which is the upskilling of resources and improvement of capabilities.

Firms that are successful will effectively use BI within their business processes to create unique capabilities, which will have a positive impact on the organisation, however there is very little studies understanding how BI systems may be effectively used to create a positive impact (Côrte-Real et al., 2014).

A recent worldwide BI maturity survey showed that only 30% of organisations within Europe, Middle East and Africa reported that in top two levels (differentiating or transformational), levels of BI maturity, and that most organisations are in levels one and two whereby a holistic organisational BI view is yet to be achieved. The report further explained that technology was not the issue. It reveals that the three biggest barriers were defining the BI strategy, determining how to measure value from BI initiative and solving risk and governance issues (Meulen, 2018).

Organisational-level benefits of BI are difficult to measure since many factors are acting on the organisation at any single time. It is difficult to isolate this factor from others. Also, for most organisations that have not implemented a big bang approach of BI. There might be pockets of successful BI implementations at departmental level which makes it difficult to gauge the overall net effect (Wixom and Watson, 2001).

The overall purpose for a maturity model is to establish an improvement roadmap moving from the current state highlighting the important variables that must be improved to reach the desired state (Eckerson, 2004).

A review of popular maturity models was done, (see Table 1-2.7-1: summary of maturity models) the criteria used was (i) how well the model was documented (ii) whether model included an assessment tool to determine how mature an organisation’s BI implementation is (iii) does the model include a technical view perspective and (iv) does the model include a business perspective. Findings show that although the TDWI Maturity Model is the most popular model with an assessment tool, it focused more on technical aspects of the warehouse and lacks a business perspective. The Gartner Maturity model also quite popular lacks the technical perspective. The Business Information Maturity Model seemed to be the best mix between technical and business, however is not very popular as the TDWI or Gartner models. The remainder of the models were not that well documented nor popularly used

	Model	Well Documented	Assessment Tool Available	Technical	Business
(Eckerson, 2004)	TDWI Maturity Model	Y	Y	Y	N
(Chuah and Wong, 2011, Chuah and Wong, 2013)	Gartner's Maturity Model	Y	Y	N	Y
(Williams and Williams, 2010)	Business Information Maturity Model	Y	Y	Y	Y
(Hagerty, 2006)	AMR Research BI/PM Model	N	N	N	Y
(Kašnik, 2008, Hribar Rajterič, 2010)	Infrastructure Optimisation Maturity Model	N	N	Y	N
(Cates, Gill and Zeituny, 2005)	Ladder of Business Intelligence	N	N	N	Y
(Sacu and Spruit, 2010)	Business Intelligence Development Model	N	N	Y	N
(Chuah and Wong, 2013)	Enterprise BI Maturity Model (EBI2M)	N	N	Y	Y

Table 1-2.7-1: summary of maturity models

The influence of agile from software development streams into business intelligence has led to a change in the normal processes of analysing, implementing and delivering BI assets into the organisation processes (Wazurkar et al., 2017). The three principles of Agile adopted from software into BI process is: (i) interactions are more important than getting the business process perfect (ii) working reports over comprehensive documentation and (iii) collaborating with the customer and instead of negotiating. Agile BI helps to realize the return on investment sooner but as decision makers are able to get value quicker and this dynamic way of working help the business evolve and adapt to changes quicker (Wazurkar et al., 2017).

The level of BI usage is low at the initial stages of BI deployment, but as the organisation becomes more analytically mature, the reliance on BI increases and so does the usage and overall value. A study by (Visinescu et al., 2017) found that provided the information quality is reasonable; the higher the usage of BI the greater the quality of decisions in the organisation (Visinescu et al., 2017).

2.8. Chapter Summary

This chapter reviewed what business intelligence is and its components. It showed how information can be used as an asset in determining business value, and reviewed literature on information quality, system quality, service quality BI competency and decision quality. It also reviewed literature on BI maturity, BI adoption and critical success factors for BI.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Research Paradigm

The term epistemology originates from a Greek word meaning knowledge. It is a philosophy of knowledge (Trochim and Donnelly, 2001) . A research paradigm is thus a framework consisting of a set of beliefs and assumptions about reality (Saunders, Lewis and Thornhill, 2012). The chosen paradigm is post-positivism which examines the observed outcomes, and then questions the reasons for certain outcomes. This paradigm is also known as reductionism whereby research challenges the causes otherwise believed as true by reflecting on the variables and testing various hypothesises through careful measurement (Yutachom, 2004). The attractiveness of this approach is that the degree of precision and prediction is higher than other paradigms and seeks rules and laws to help understand (Grix, 2010).

3.2 Research Design

Epistemology and methodology are closely related. One refers to the philosophy of knowing and the other is the practice (Trochim and Donnelly, 2001). Research design is the plan, consisting of the structure and the process, or strategy of the study with the objective to answer the research questions (Singh, 2007).

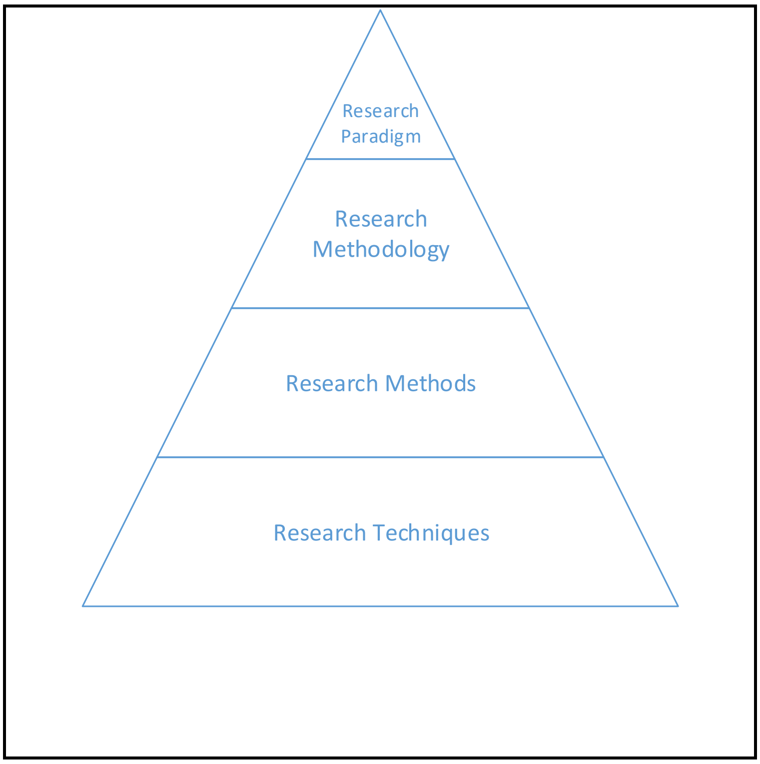


Figure 3.2-1: The research pyramid – adapted from (Jonker and Pennink, 2010)

This research pyramid shows a breakdown of how the research was designed. A top-down view reveals the chain of choices from an abstract paradigm; then to a methodology, to research methods and then lastly concrete techniques (Jonker and Pennink, 2010). For this study, the quantitative methodology was chosen since the primary aim is to test hypotheses from existing theories and examine relationships between the dependant and independent variables. The study follows the quantitative methodology and adopts a descriptive research design rather than a causal. It is a cross-sectional study which is a snapshot of a sample which represents a population being studied. Therefore, this particular study does not seek to establish cause.

3.3 Research Strategy

Quantitative research is characterised by examining existing theories, identifying variables, operationalising the variables in study and measuring them using survey methods. This then should be followed by analysing using statistical methods to gauge the degree of influence and impact (Sekaran and Bougie, 2016, Grix, 2010).

Figure 3.3-1: Flow of quantitative research - adapted(Jonker and Pennink, 2010)

Several theories relating to critical success factors in business intelligence - maturity models and technologies adoption models - were reviewed. Relevant variables for the metals rolling industry with a low maturity level were chosen. This formed the basis for the dependant variables which the study sought to understand. Several hypotheses were created based on the outcomes of existing literature. A survey instrument which can serve as a continuous improvement assessment tool was created from mostly existing questionnaire questions from existing theories. The survey was distributed *via* an email link, with the informed consent attached whereby participants could fill in the responses. Once sufficient responses are received and a period of two weeks elapsed, the responses were analysed using SPSS. Correlation techniques were applied to measure strengths of any relationships. The hypotheses were tested for validity against existing theories and findings.

3.4 Research Setting

This study was conducted in a public company Hulamin with headquarters in Pietermaritzburg KwaZulu-Natal. It is a semi-manufacturing aluminium rolling plant listed on the JSE. It deals in both local and international exports of rolled coils to consumer conversation plants which create end products such as vehicles, aluminium beverage cans, foils, cookware, extruded aluminium products, and so forth. The Pietermaritzburg headquarters consists of two connected manufacturing sites namely; Campsdrift (hot rolling) and Edendale (cold rolling). There are other manufacturing sites in Johannesburg and Pretoria but the study only focuses on the two

Pietermaritzburg sites. There are approximately 2,000 employees' onsite. However, only those workers with a valid SQL server reporting services client access licence and sufficient report runs were considered in this study.

Hulamin embarked on implementing a business analytics implementation about five years ago. It was a phased approach focusing on key departments and then spread out to other departments. There is a dedicated business intelligence team which forms part of the larger information technology department.

3.5 Target Population

A BI usage report indicates that only 67 users out of the BI licenced users reflected sufficient report runs (Hulamin, 2018), this represents the population for our study. For the purposes of this study, the focus is on BI use and how it affects decision making if any. Therefore, since the entire population is so small, the entire population will be used in the research.

3.6 The Research Instrument

The research instrument was a self-administered survey questionnaire. The survey was created as a survey list (tool within SharePoint) and was accessible to all participants in the sample *via* a direct link which was emailed. Web surveys offer several advantages over traditional methods like print, postal-mail surveys and telephone surveys. Advantages include that it has lower costs, it offers faster turnaround times, offers more reliable data from validation, ability to export results data into analysis tools, more convenience for researcher offering quick and timely dissemination and it is aimed at larger sample sizes (Parsons, 2007, Saunders et al., 2012). The choice of an intranet hosted survey as opposed to an external tool like Survey Monkey is accessibility, and most users are not allowed to view external sites. However, the intranet is available and most users are already familiar with the site. The disadvantages of the web-based survey is the technological challenge and literacy that the participants have to overcome and not appropriate for all instances and suffers from lower response rate (Parsons, 2007). However, considering both the advantages and disadvantages, the web survey method is ideal for the research at hand.

3.6.1 Survey Instrument Design

Measurement in terms of research assigned numbers to represent observable outcomes, objects or properties using a set of rules. It is a three step process: (i) selecting observable outcomes, (ii) developing mapping set of rules for assigning numbers to the outcome been measured, (iii) applying the mapping rules to the outcome (Cooper and Schindler, 2014). The questionnaire contained six sections to test the constructs and how they related to decision making. These sections are: information quality, report quality which is a measure of system quality, ease of use, usefulness, BI Service Quality and BI competency. The close-ended questions on a Likert scale were used to collect responses because it reduces the amount of cleaning or coding needed in analysis. The survey was in the form of an online survey hosted on the company's intranet which is accessible to the employees. The technology used is SharePoint Survey Lists which uses access control according to active directory permissions, and therefore, it is well secured and not accessible outside the allowed group. It is also not available on the internet and is secured behind a firewall.

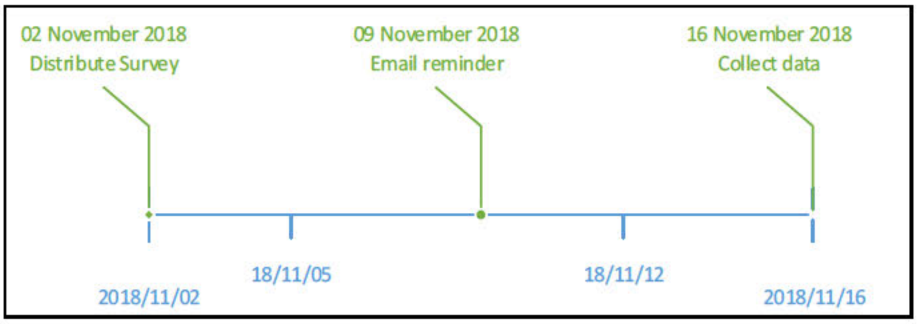
The interval scale is deployed using the five points from strongly disagree, disagree, neither agree nor disagree, agree and strongly agree.

Options Answer	Score
Strongly disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly agree	5
Not applicable	Missing

The informed consent was built as the opening screen of the survey conveying to the participants that their participation was voluntary and that their information would be kept confidential and used only for research purposes. The participant then can choose if they agree with the terms in the informed consent by clicking on "I agree" and submitting, afterwards the start of the survey will be presented, or alternatively clicking on "I do not agree and submitting will close the window and no survey will be presented. The informed consent will also be emailed as an attachment as part of the participant invitation email. The response rate was 64.1%, which represents 47 responses out of a total of 67.

3.6.2 Data Collection

There was an invitation email with the body briefly introducing the study including the objectives and a link to the survey. The informed consent letter was attached, and participants were redirected to the survey cover page when the link was clicked.



The period of data collection was envisaged to be two weeks starting on a Friday. A reminder email was sent after the end of the first week. The survey was designed to be completed within

20 minutes, built in validation to facilitate that there is a response for each question. The survey results were imported into SPSS for analysis.

3.7 Data analysis

Validation was built into the SharePoint survey list to ensure that a response for every question was chosen otherwise it would not allow submission. This eliminated missing responses from the results and half completed surveys. The data from these SharePoint lists were exported into SPSS and cleansed for missing values. The data was then analysed quantitatively, testing for correlations and testing hypothesis.

3.8 Validity

There are two alternatives of validity. External validity is the ability to generalise the results to the wider population. Internal validity refers to how effectively the research instrument is able to measure what it is intended to measure in the study. The three types of validity are content validity - criterion related, and construct validity (Cooper and Schindler, 2014, Creswell, 2013).

Content validity is the extent of coverage to which the questions guiding the research are adequate. This can be achieved by deciding what factors are influencing efficient an effective decision-making using BI. This can be done by the researcher using intuition and past studies, or through a panel of judges. For the current study, the researcher based the content and questions on several past theoretical studies of similar nature which were deemed to be content valid and reliable.

Content related criterion validity is the degree to which measures agree with external criterion, that is how much it is a predictor of outcome of interest, any validity criterion used must be subjected to four qualities are (i) is it relevant in terms of a success measure, (ii) is it free from bias, (iii) is it stable or repeatable and (iv) is it available.

Construct validity is concerned with the variance in measure. If results are consistent with the theoretical concept being measured, it is assessed through convergent and discriminant validity. In this study, the selection of questions where chosen from existing studies and were adapted for the specific context. Therefore, it should be valid. The convergent validity was shown when the results of the survey were weighed against other questionnaires measuring the same constructs in different studies. Discriminate validity was shown when unrelated variables were empirically found to be uncorrelated.

3.9 Reliability

To test the reliability and validity of the measurement instrument (the survey), the Cronbach coefficient alpha was used. It was important to report on the internal consistency of the scale otherwise the results would not be trusted. Each main construct had several sub-constructs (multi-dimensional) relating to the main construct. However, each sub-construct carried with it a certain level of error in respect to measuring the actual main construct. A good scale tries to minimise this error value.

There are several types of reliability. The test-retest method requires that participants answer the same test several times. The acceptable different between the two or many scores should be around 15. Also, the rule of thumb is to wait 15 days to a month before the re-test (Saunders et al., 2012). The parallel form follows the same approach as the test-retest with the exception that the second test is slightly shuffled from the first test. However, this was not deemed feasible due to time constraints.

Cronbach's alpha is the most popular method of internal consistency which is the degree to which the questions are aligned to reflect the underlying constructs. A score above 0.7 is considered reliable (Leech, Barrett and Morgan, 2014).

A pilot test of the questionnaire was given to seven users within the IT department whom utilize BI reports, the purpose was to gauge the ease of understanding of the questions. Few questions which contained technical jargon were revised, and finalized.

3.10 Elimination of Bias

3.10.1 Researcher Bias

Researcher bias can mislead the participant from the research objectives. Several biases can exist in the instrument, and no research is truly free from bias. However, two such researcher biases were identified in this research. The first was the order question bias whereby the answer of the previous question influenced the next question. Ideally, separating these two questions with a general question remedied the bias. Secondly is the loaded question bias whereby the researcher reflects their bias in the question to get a desired response (Singh, 2007). In this study, the questions were logically grouped into the sections under study to avoid order question bias. In addition, the questions in this study were adapted from previous studies and thus reduced the loaded questions researcher bias.

3.10.2 Selection Sampling Bias

Selection bias occurs when the researcher chooses a sample which is not a fair representation of the population, hence the results are often skewed (Saunders et al., 2012). This bias was eliminated since the entire population was used as the sample.

3.10.3 Response Bias

Response bias can exist when there is less than a 100% response rate to voluntary surveys. This bias increases the lower the response rate. It raises the question as to whether the non-respondents feel different to those that responded. The researcher must therefore design the study to try and maximise the response rate (Grix, 2010, Lapan, 2003). Assuring anonymity and having a random sample reduces the chances of non-responses. Reminder emails also limited the amount of non-responses. In this study there were 24 non-responses which makes up 35.8% of the population, response bias was reduced as it was done anonymously.

3.11 Ethical Considerations

A "request for permission to conduct research in Hulamin" letter detailing the title and nature of research was handed to the Senior IT Manager explaining what the research is and how it would benefit the organisation. The explanation also identified the gatekeeper, in this case, the BI manager who would oversee the study. The senior IT manager as well as the gatekeeper signed an "approval of research" response letter stating the conditions under which the research procedure would abide by in terms of safety rules, informed consent and Hulamin protocols, also advised that the researcher would work with the BI manager once the study was ready to commence.

An informed consent to participate letter was prepared. According to the general guidelines, in order to ensure that participation is voluntary, non-monetary, anonymous and confidential, data collected was only used for the purpose of the research.

An ethical clearance application was submitted and based on outcome. The data collection may begin. The chosen sample users received emails describing the nature of the study, how the data would be used. The emails contained the attachment of the informed consent in PDF format.

The first page of the online SharePoint Survey List displayed information about the purpose of the study and how the data would be kept confidential and used only for the research purpose. It would have a link to the informed consent which was in PDF form. Consent was achieved by actual participation. In the informed consent, the last paragraph denoted "Since this is online survey, by completing the questionnaire, you are consenting to take part in the study."

After reading, at the bottom of the page, a section with terms and conditions was displayed with two options of "I agree" or "I do not agree" and a submit button. If the participant chose "I agree" the survey questions were presented and they could be proceed, otherwise if "I do not agree" is chosen on submit, the page would close and there would be no participation.

3.12 Chapter Summary

This chapter showed how the research would be executed with rigour following a scientific methodology using a quantitative method which entailed a research instrument in the form of an online questionnaire with five level Likert scales. The chapter described the population, sampling techniques, research settings and how researcher would overcome any biases that might occur. The collected data was analysed using SPSS package and relationships relating to the hypothesis.

The next chapter presents the results of the study.

CHAPTER FOUR: RESEARCH ANALYSIS & FINDINGS

4.1 Introduction

The chapter deals with the analysis of the data that collected. The research sample which was also the entire population included 67 participants that were surveyed utilising a self-administered questionnaire hosted on the company's intranet. Data analysis in this section is split into descriptive and inferential statistics. The results of the survey are analysed according to the following research constructs: a) Information Quality, b) System Quality, c) BI Service Quality, d) BI Competency, e) Decision Quality. Questions under the various constructs form the building blocks in understanding which factors influence the quality of decision making, if any.

4.2 Descriptive Statistics

4.2.1 Demographics

The demographic analysis presented below is representative of gender, age, and years of experience using business intelligence reporting as well as management indicator and frequency of usage.

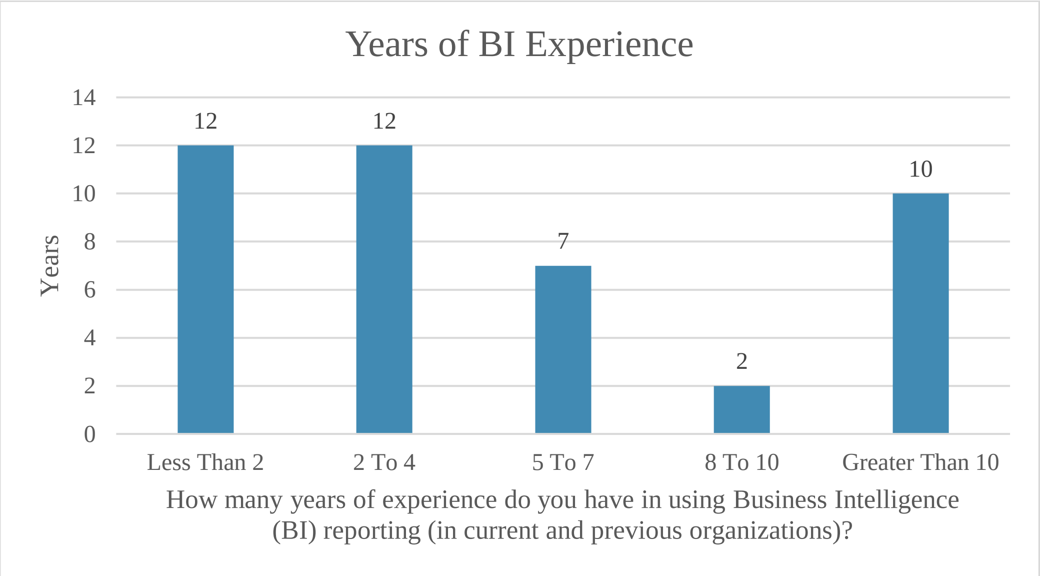


Figure 4.2-1 – The categories of experience in years using business intelligence

Figure 4.2-1 above shows that ranges of BI experience in years that the sample contains. It is evident that the largest group have under two years of experience using any form of business intelligence within the current and or previous organisations. However, there is a significant group of people with BI experience of greater than 10 years which means that there is a good percentage of experienced BI users in the organisation. There is almost an even percentage of managers versus non-managers in the sample.

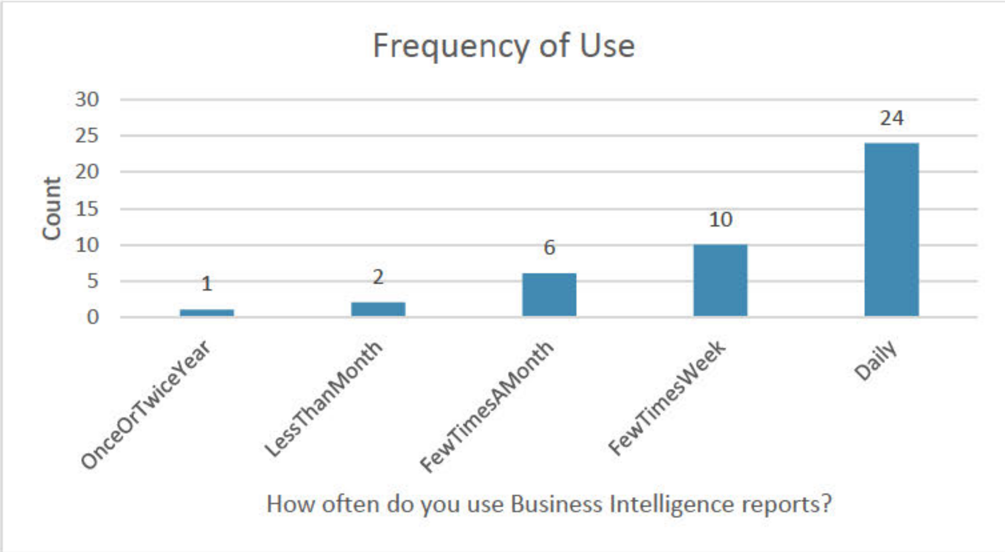


Figure 4.2-2 - Histogram showing frequency of BI use in organisation

Figure 4.2-2 shows that most of the respondents in the sample use BI daily, with the second highest group showing usage of a few times a week.

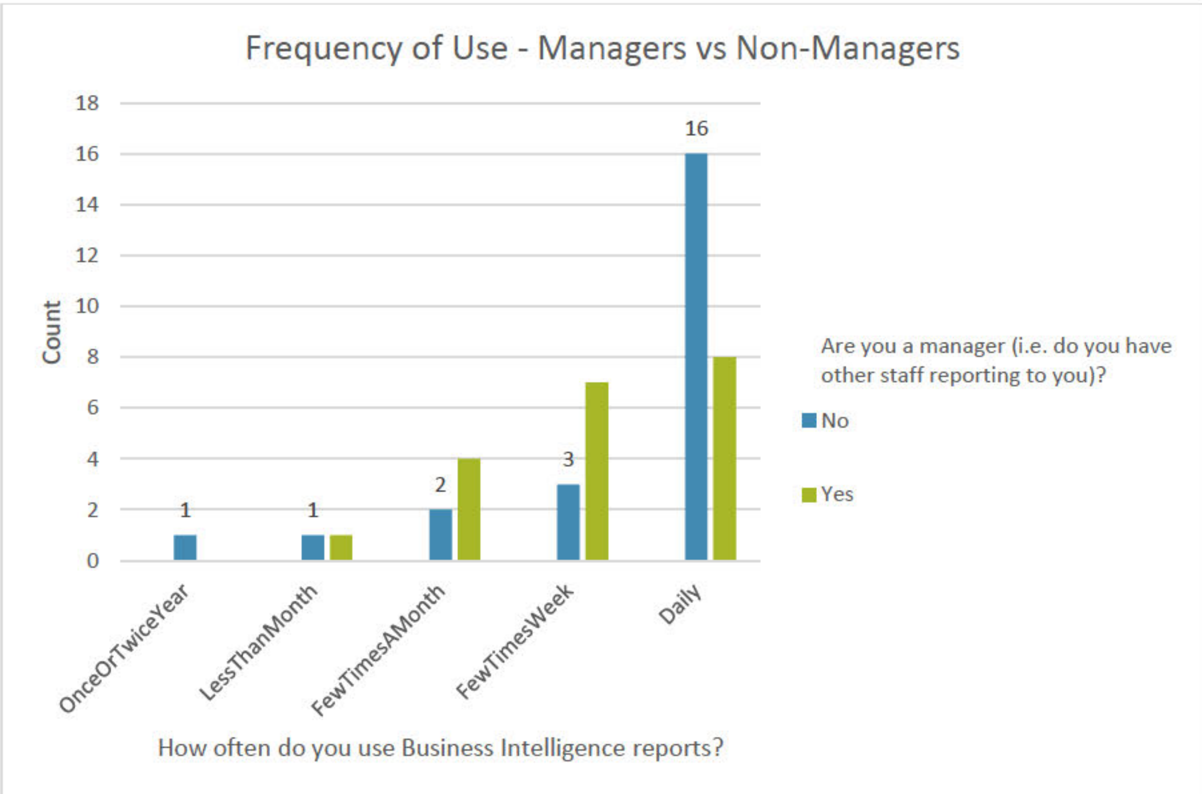


Figure 4.2-3 - Frequency of BI use by managers and non-managers

Figure 4.2-3 shows that non-managers have the highest daily use, whilst the highest weekly usage is that of managers. This could imply that managers use the summarised level of detail, thus less frequently whilst non-managerial use BI as part of their normal processes.

4.2.2 Research Construct 1 – Information Quality

Information quality, from the viewpoint of the consumer, would be defined as the degree of fitness for its intended application (Brodie, 1980). It is a multi-dimensional construct (Wang and Strong, 1996) and for the purposes of this study, it is interchangeable with data quality.

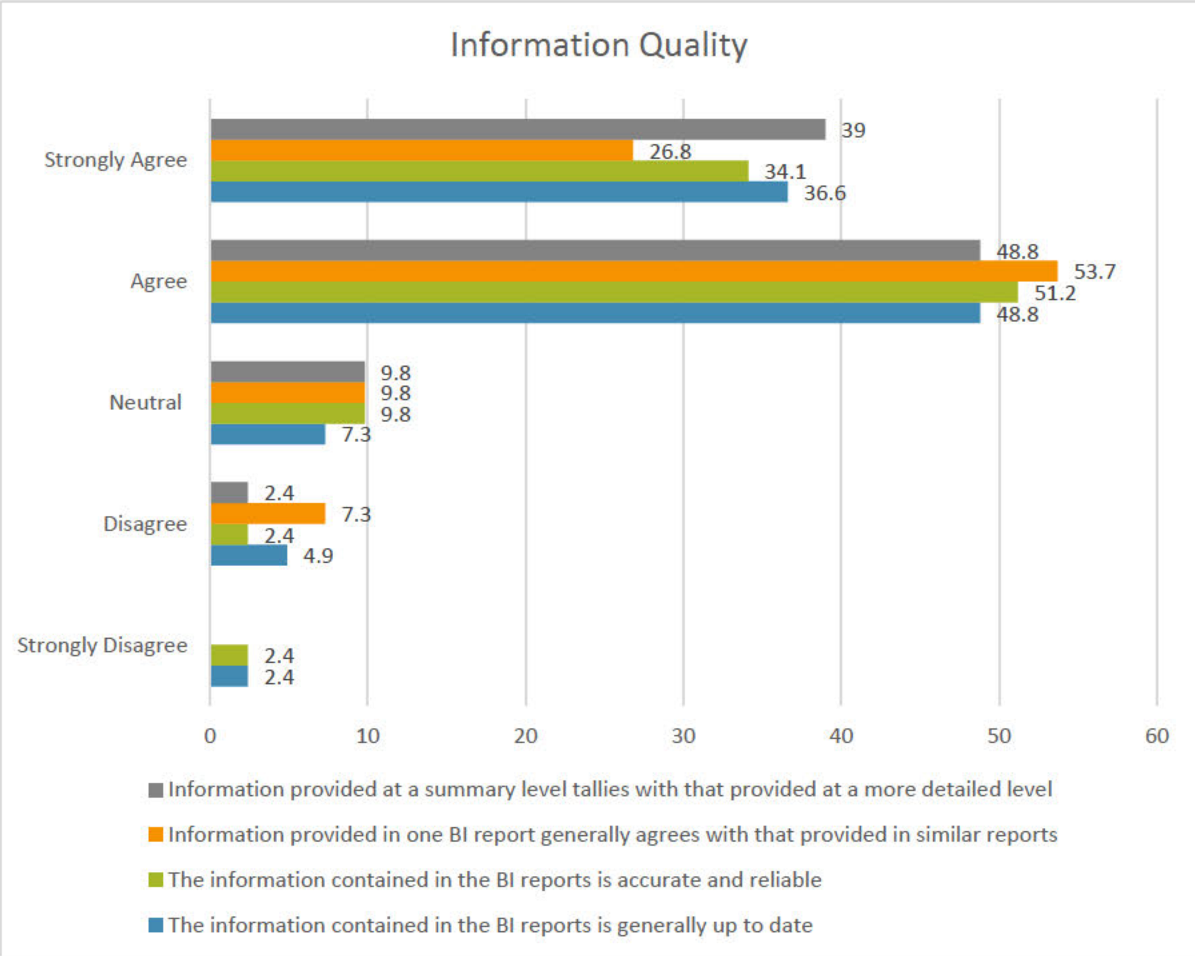
#	Question	Construct	Reference
IQ1	The information contained in the BI reports is generally up to date	Timeliness	(Wang and Strong, 1996)
IQ2	The information contained in the BI reports is accurate and reliable	Accuracy	
IQ3	Information provided in one BI report generally agrees with that provided in similar reports	Relevancy	
IQ4	Information provided at a summary level tallies with that provided at a more detailed level	Representational consistency	

Timeliness is a measure under the contextual data quality category. It determines how current the data is (Wang and Strong, 1996). The results show that 85.4% of the sample agree or strongly agree that the data contained in the reports are timeous. However, about 7.3% of the sample seem to think that the data contained in reports are stale.

Accuracy is a measure under the intrinsic data quality category. It is the extent to which information is correct and free from errors (Wang and Strong, 1996). The results show that 85.3% of the sample agree or strongly agree that the data is accurate whilst 4.8% indicate that data is not accurate.

Traceability and relevancy are measures under the contextual data quality category. It measures how appropriate the data is to the task at hand and the extent to which it is attributable to a source (Wang and Strong, 1996). The results showed that 80.5% either agreed or strongly agreed whilst 7.3% disagreed.

Representational consistency is a measure under the representational data quality category. It measures the extent to which data is compatible with other data and presented in a consistent format (Wang and Strong, 1996). A total of 87.8% agreed or strongly agreed whilst 2.4% disagreed.



There were four questions that determined the information quality measure, values 4 and 5 represented agree and strongly agree on the Likert scale.

Table 4.2-1: Frequency Distribution for Information Quality indicates72.1% *(100 – 27.9%)* of participants tended to agree with statements on information quality.

Table 4.2-1: Frequency Distribution for Information Quality

Information Quality			
	Frequency	Percent	Cumulative Percent
8	1	2.3	2.3
9	1	2.3	4.7
11	1	2.3	7.0
12	1	2.3	9.3
14	2	4.7	14.0
15	6	14.0	27.9
16	11	25.6	53.5
17	6	14.0	67.4
18	4	9.3	76.7
19	2	4.7	81.4
20	8	18.6	100.0
Total	43	100.0	

4.2.3 Research Construct 2 – System Quality

System quality refers to the quality of the actual system. It is mostly engineering and design-orientated characteristics of the system such as system accuracy, flexibility, convenience of access, and ease of use (DeLone and McLean, 1992).

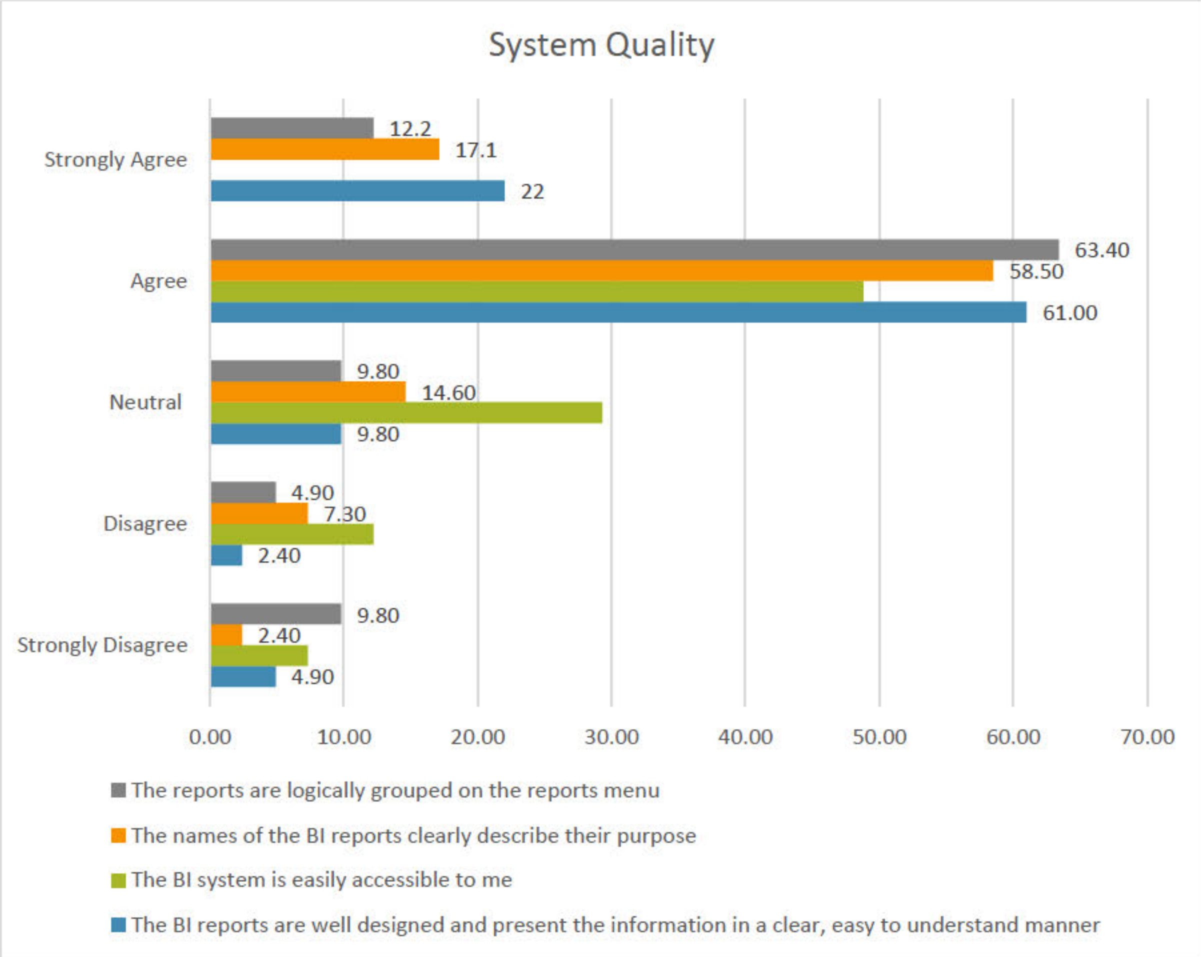
#	Question	Construct	Reference
SYQ1	The BI reports are well designed and present the information in a clear, easy to understand manner	Ease of Use	(DeLone and McLean, 1992)
SYQ2	The BI system is easily accessible to me	Convenience of access	
SYQ3	The names of the BI reports clearly describe their purpose	System accuracy	
SYQ4	The reports are logically grouped on the reports menu	Ease of learning	

Ease of use include usability aspects such as design, easy to understand and choice of visualisation of data, results show that 83% of the sample agree or strongly agree whilst 7.3% disagree or strongly disagree.

Convenience of access falls into accessibility category of system quality. Results show that 78.1% agree or strongly agree whilst 9.7% disagree. This issue could be related to a monthly automatic password expiry policy in Hulamin, whereby a user has to change their password monthly for security purposes. This could deny access to reporting as the BI system uses the AD credentials of the logged in user which would have been expired.

System accuracy is the degree to which the BI system is free from errors and represents data correctly. In this case, the question related to the name of the report relaying the semantic of what the report is about. Results show that 75.6% agree or strongly agree whilst 9.7% disagree or strongly disagree. Some BI systems restrict the number of characters in a report title. However, SQL reporting services does not have this restriction. Thus, this could imply that some reports have badly named titles.

Ease of learning includes aspects like how intuitive is the reporting tool. It will assess how well the user can easily find the report they are seeking without any assistance. This question measures the ease of learning. Results show that 75.6% agreed or strongly agreed whilst 14.7% disagreed or strongly disagreed. This could reflect an underlying cross departmental issue of technical jargon whereby one department refers to the same construct with a different term to the other department, and often there is information that overlaps.



There were four questions that determined the system quality measure, values 4 and 5 represented agree and strongly agree on the Likert scale. Table 4.2-2 - Frequency Table for Total System Quality indicates 65.1% of participants agreed with statements on the system quality.

System Quality			
	Frequency	Percent	Cumulative Percent
4	1	2.3	2.3
7	1	2.3	4.7
10	1	2.3	7.0
11	1	2.3	9.3
12	1	2.3	11.6
13	1	2.3	14.0
14	6	14.0	27.9
15	3	7.0	34.9
16	10	23.3	58.1
17	8	18.6	76.7
18	5	11.6	88.4
19	4	9.3	97.7
20	1	2.3	100.0
Total	43	100.0	

Table 4.2-2 - Frequency Table for Total System Quality

4.2.4 Research Construct 3 – BI Team Service Quality

Service quality is focused on the efforts of the IT team in providing the information product (information provider) and supporting end users (service provider) (Delone and McLean, 2003, Karlinsky-Shichor and Zviran, 2016).

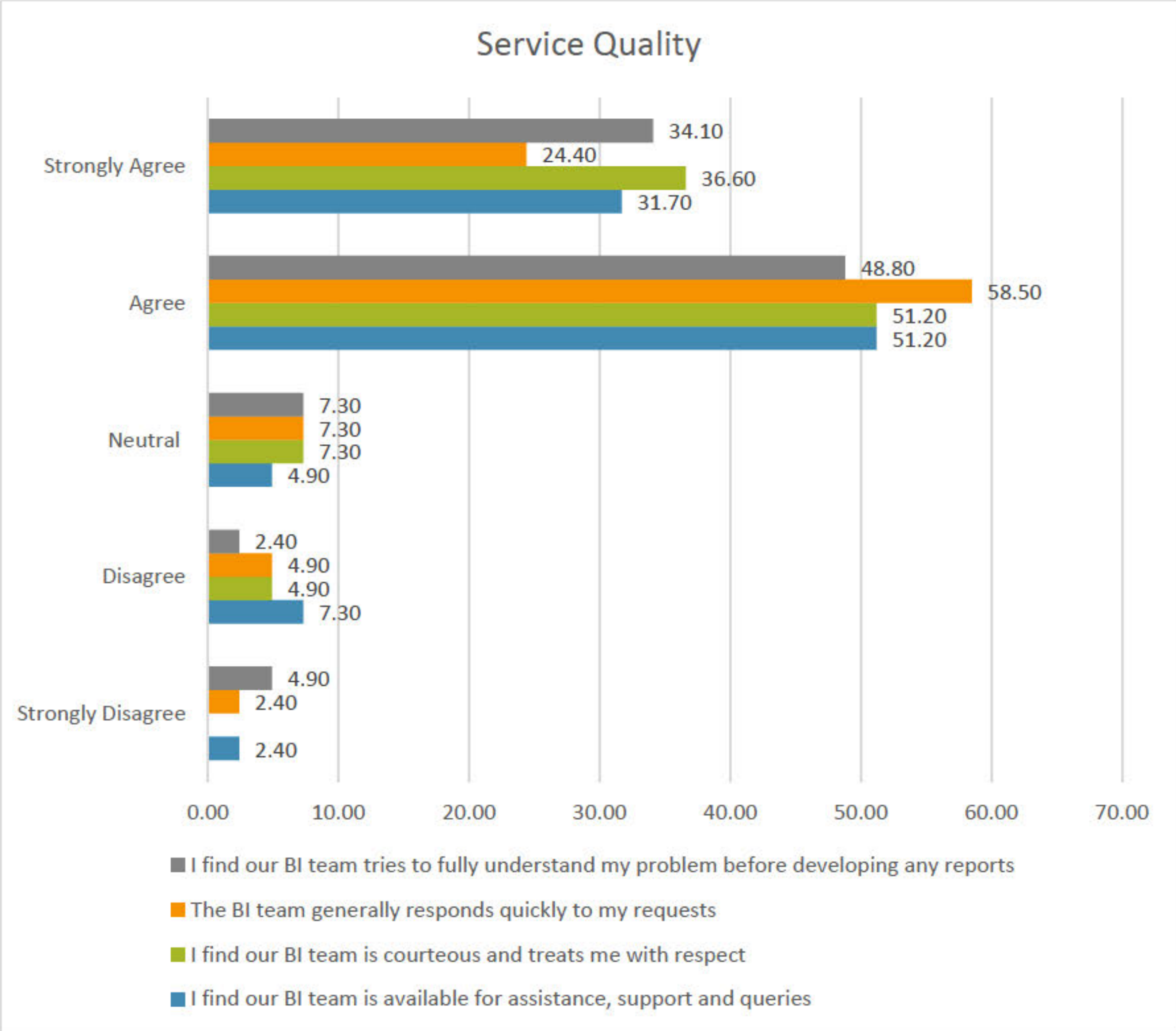
#	Question	Construct	Reference
TSQ1	I find our BI team is available for assistance, support and queries	Availability	(Fink et al., 2017)
TSQ2	I find our BI team is courteous and treats me with respect	Interpersonal skills	
TSQ3	The BI team generally responds quickly to my requests	Turnaround time	
TSQ4	I find our BI team tries to fully understand my problem before developing any reports	Domain knowledge	

Availability refers to how available support structures and teams are to attend to support queries. Results show that 82.9% agree or strongly agree that BI team is available for support queries whilst 9.7% disagree or strongly disagree. Since BI is relatively in the adoption phase, whilst there is a large growing demand, the team often is constrained with priorities and limitations.

Several authors concur that collaboration between analysts, data scientists and decision-makers leads to better quality decision making (Janssen et al., 2017). Thus, interpersonal skills of the BI team is paramount to the quality of decision making. Results show that 87.8% of respondents agree or strongly agree whilst 4.9% disagree.

Turnaround time is the time from obtaining a report request to deploying the information product. It is an important measure for the dynamic capability of the firm and its uniqueness that makes it to be competitive (Lee, Xu, Kuilboer and Ashrafi, 2012). Results show that 82.9% of respondents agree or strongly agree that the turnaround time is quick whilst 7.3% disagree or strongly disagree.

Domain knowledge is a valuable rare skill of the analyst to completely understand the business domain. It adds to the firm's dynamic capability, and was shown by the results of the study as ca[able of leading to better quality decision making and performance (Torres, Sidorova and Jones, 2018, Tai et al., 2018). Results show that 82.9% of respondents agree or strongly agree whilst 7.3% disagree or strongly disagree. Domain knowledge is closely related to years of experience in the domain. It includes both explicit and implicit knowledge.



There were four questions that determined the BI team service quality measure. Values 4 and 5 represented agree and strongly agree on the Likert scale. Table 4.2-3 - Frequency Distribution for BI Team Service Quality indicates 72.1% of participants agreed with statements on the BI team service quality.

BI Team Service Quality			
	Frequency	Percent	Cumulative Percent
4	1	2.3	2.3
5	1	2.3	4.7
6	1	2.3	7.0
11	2	4.7	11.6
12	3	7.0	18.6
14	1	2.3	20.9
15	3	7.0	27.9
16	11	25.6	53.5
17	6	14.0	67.4
18	4	9.3	76.7
19	6	14.0	90.7
20	4	9.3	100.0
Total	43	100.0	

Table 4.2-3 - Frequency Distribution for BI Team Service Quality

4.2.5 Research Construct 4 – BI Competency

BI competency is the range of possible tools, sophistication of analysis techniques and visualisations mediums that are available to an organisation to mobilise and deploy BI functionalities (Wieder and Ossimitz, 2015, Ramakrishnan et al., 2016)

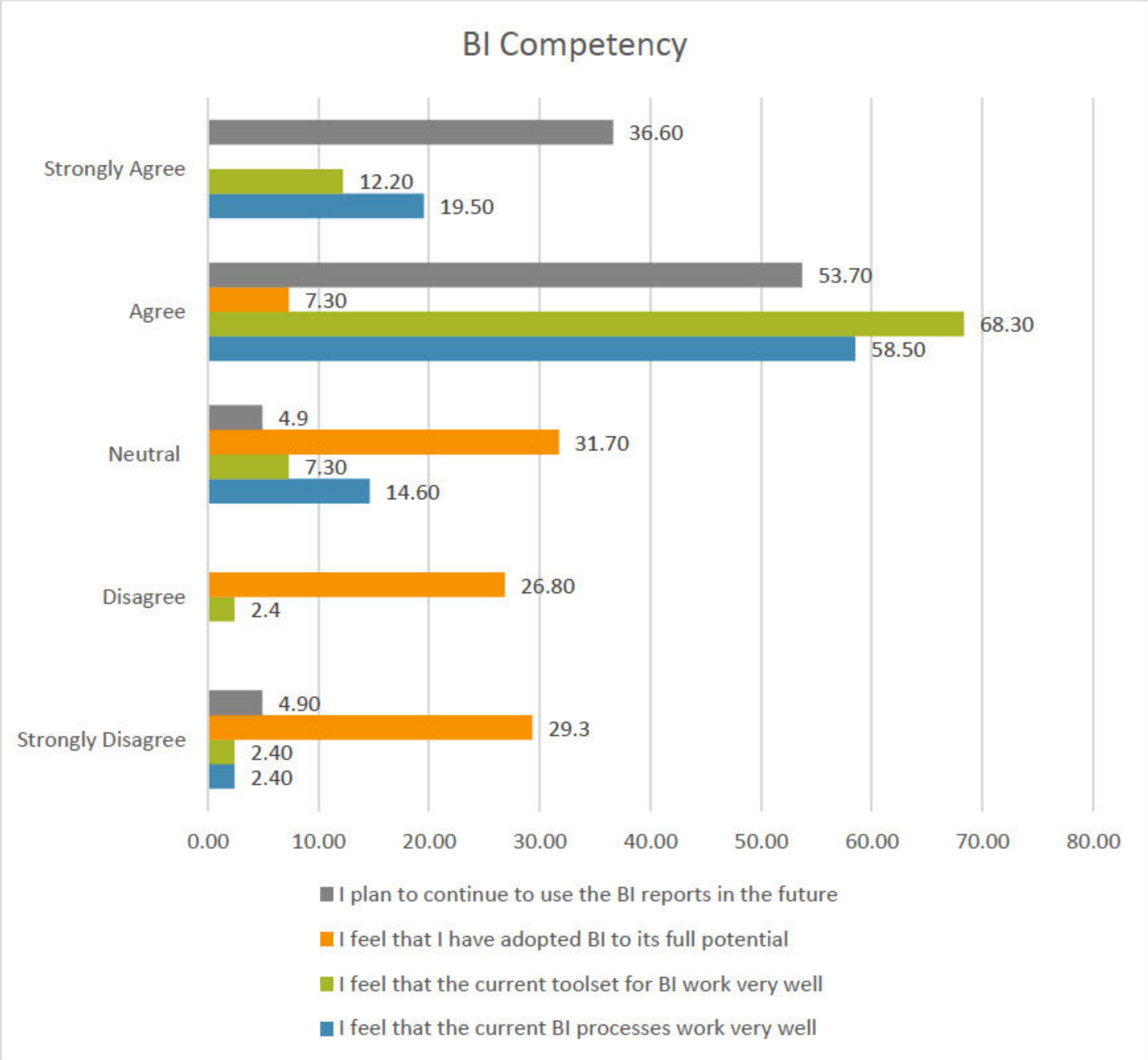
#	**Question**	**Construct and Reference**
BIC1	I feel that the current BI processes work very well	BI Process & integration Capability - (Ramakrishnan et al., 2016)
BIC2	I feel that the current toolset for BI work very well	Tool sophistication (Ghasemaghaei et al., 2018)
BIC3	I feel that I have adopted BI to its full potential	Analytical Skills - (Ghasemaghaei et al., 2018)
BIC4	I plan to continue to use the BI reports in the future	Application Use - (Foshay, Taylor and Mukherjee, 2014)

BI process and integration capability fall under BI operational capability, and it is the ability to use BI assets efficiently to achieve operational goals. It also enhances organisational learning and innovation, a process which is understood as the extent to which knowledge is gained from the existing processes. The results show that 78% of the sample agree or strongly agree while only 2.4% disagree.

Tool sophistication refers to the variety and complexity of the BI tools. It ranges from basic descriptive reporting and dashboards to predictive - which contains sophisticated statistical and forecasting capabilities to prescriptive which suggest alternative optimum decision paths to choose. The results show that 80.5% agree or strongly agree that the current tool sophistication works well, while 4.8% disagree or strongly disagree. The organisation currently uses mostly descriptive analytics with just a single application optimising the electricity costs, using advanced predictive analytics.

The analytical skills are the competency of the organisation to support systematic decision making for sophisticated decision-making in scenarios such as strategic planning whereby analyst support is called upon to advise senior management on alternatives which may be pursued. Interpreting complex predictive and prescriptive outputs require technical skills to understand the method and the levels of impact that will be effected by each action on variables (Cao et al., 2015). Results show that only 39% of respondents agreed or strongly agreed that they had fully incorporated BI capability to the maximum. BI currently offer several additional models of analysis such as power BI (self-service application). However, most users are only familiar with the BI reporting analytics. Results show that 34.3% disagree or strongly disagree that they have adopted BI to its full potential. This indicates that they are aware that there are more analytical capabilities available at their disposal but only utilise a few.

Several adoption models concur that behavioural intension leads to actual use, and that the measure of success of a system is ultimately determined by the use. In the case of the BI system, the behavioural intension is a measure of use which will be transcribed to systematic decision-making and finally better firm performance (Delone and McLean, 2003, Côrte-Real et al., 2014). Results show that 90.3% of the respondents agree or strongly agree that they will continue to use BI in the future. This is an indicator that the organisation is adopting a data-driven culture diffusing outward. Only 4.9% indicated that they strongly disagreed with using BI. This could indicate that the sample contained a disgruntled employee with a bad experience whilst the majority of participants utilized BI.



There were four questions that determined the BI competency measure. Values 4 and 5 represented agree and strongly agree on the Likert scale. Table 4.2-4: Frequency Distribution of BI Competency indicates 51.2% of participants agreed with statements on the BI competency.

BI Competency			
	Frequency	Percent	Cumulative Percent
3	1	2.3	2.3
6	1	2.3	4.7
8	1	2.3	7.0
9	2	4.7	11.6
12	2	4.7	16.3
13	2	4.7	20.9
14	3	7.0	27.9
15	9	20.9	48.8
16	14	32.6	81.4
17	3	7.0	88.4
18	2	4.7	93.0
19	2	4.7	97.7
20	1	2.3	100.0
Total	43	100.0	

Table 4.2-4: Frequency Distribution of BI Competency

4.2.6 Research Construct 5 – Decision Quality

Organisational scientific enquiry or rational thinking is defined as the actions of firms to seek truth, exercising higher order reasoning and take appropriate actions to pursue economic goals (Power, 2016). A good decision is often measured by the outcome, and the quality depends on the process of systematically reviewing all the options and conducting a due diligence.

#	Question	Construct and Reference
DQ1	I can usually find a report that provides me with the information I am looking for	Data driven decision making (Cao et al., 2015)
DQ2	I find that the BI reports are flexible and allow me to retrieve the information I need in an appropriate way	Systematic processing behaviour (Kowalczyk and Gerlach, 2015)
DQ3	Using the BI reports enables me to make decisions more quickly	Decision efficiency - (Ghasemaghaei et al., 2018)
DQ4	Using the BI reports enables me to make better business decisions	Decision Quality - (Ghasemaghaei et al., 2018)
DQ5	Using the BI reports increases my business productivity	Decision efficiency - (Ghasemaghaei et al., 2018)
DQ6	I consider my usage of the BI reports to be beneficial to Hulamin	Decision quality (Kowalczyk and Gerlach, 2015)
DQ7	Using BI reports has brought to light new information/insights which were previously not evident	Data driven decision making (Cao et al., 2015)
DQ8	BI is fully integrated into my existing business processes	BI process capability - (Ramakrishnan et al., 2016)

Data-driven decision making is often embedded into the organisational culture as part of the processes to consider when making decisions to use a systematic process instead of relying on intuition. Results show that 75.6% strongly agree or agree, whilst 12.2% disagree or strongly disagree. This indicates that the majority of decision-makers have the required BI assets they require for the task at hand while a few decision-makers lack adequate information relating to the task at hand, and therefore will revert to some other method such as intuition. This could signal that BI assets to support a particular task is not yet developed.

Systematic processing implies following a rigid process, considering all the options and selecting the appropriate one based on the desired outcome. Results show that 80.5% agree or strongly agree that they follow a systematic process while 9.8% indicate that they disagreed or strongly disagreed.

Decision efficiency is the speed and reduction of effort at which a decision can be made based on sufficient evidence. Results show that 87.8% of the respondents agreed or strongly agreed that BI enables decision efficiency while 7.3% disagree or strongly disagree. This could be viewed with question 1, in that, BI assets related to the task at hand will have not been deployed yet.

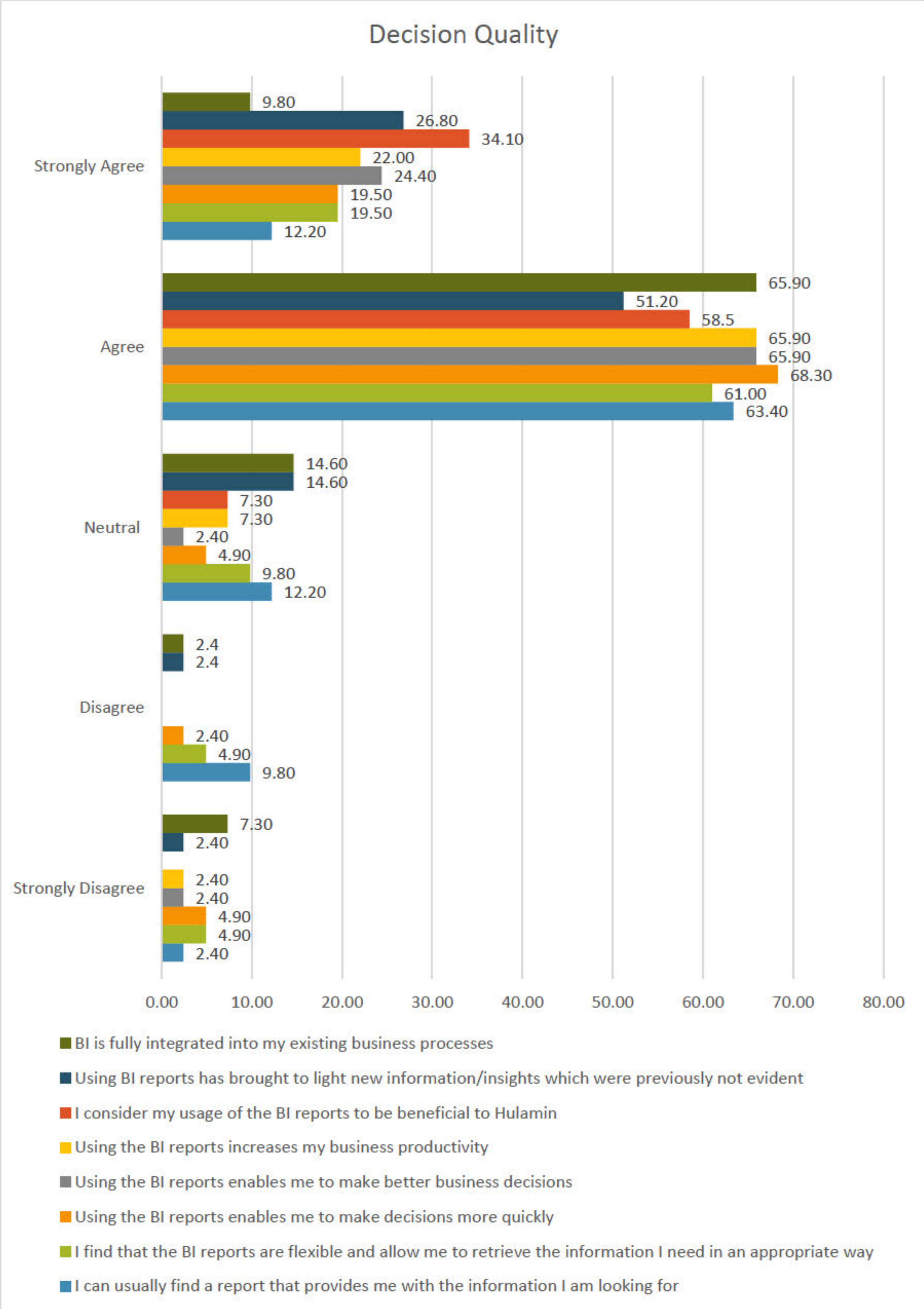
Decision quality is the effectiveness of the outcome to achieve a goal. Results show that 90.3% agree or strongly agree that BI enables a high quality of decision making. This is an important result in the decision quality category. Only 2.4% indicate that it did not enable better quality decisions. This could be the result of a single disgruntled user.

BI increasing business productivity is a measure of decision efficiency by reducing the amount of work needed to get information, or alternatively by actively managing business processes to optimise processes using BI as a measurement tool. Results show that 87.9% agree or strongly agree whilst only 2.4% disagree.

Decision quality and importance, is an employee perception on the impact of BI on decision making, results show that 92.6% agree or strongly agree that BI reports are beneficial to Hulamin, and zero believe otherwise.

Data driven insights is the ability of BI to find hidden patterns embedded in data and present it as insights to the decision maker. Results show that 79% agreed or strongly agreed that BI offers new insights whilst 4.8% disagreed or strongly disagreed.

BI process capability is the capability of the organisation to embed into their daily activities the use of BI as part of the decision-making process. Results show that 75.7% agreed that BI is fully integrated into their existing processes whilst 9.7% disagreed or strongly disagreed.


Decision Quality
Strongly Agree
Agree
Neutral
Disagree
Strongly Disagree
9.80
26.80
34.10
22.00
24.40
19.50
19.50
12.20
65.90
51.20
58.5
65.90
65.90
68.30
61.00
63.40
14.60
14.60
7.30
7.30
2.40
4.90
9.80
12.20
2.4
2.4
2.40
4.90
9.80
7.30
2.40
2.40
2.40
4.90
4.90
2.40
0.00
10.00
20.00
30.00
40.00
50.00
60.00
70.00
80.00
BI is fully integrated into my existing business processes
Using BI reports has brought to light new information/insights which were previously not evident
I consider my usage of the BI reports to be beneficial to Hulamin
Using the BI reports increases my business productivity
Using the BI reports enables me to make better business decisions
Using the BI reports enables me to make decisions more quickly
I find that the BI reports are flexible and allow me to retrieve the information I need in an appropriate way
I can usually find a report that provides me with the information I am looking for

There were eight questions that determined the decision quality measure. Values 4 and 5 represented agreed and strongly agreed on the Likert scale. Table 4.2-5: Frequency Distribution of Total Decision Quality indicates 60.5% of participants agreed with statements on the decision quality.

Decision Quality			
	Frequency	Percent	Cumulative Percent
11	1	2.3	2.3
20	2	4.7	7.0
24	2	4.7	11.6
27	2	4.7	16.3
29	4	9.3	25.6
30	1	2.3	27.9
31	5	11.6	39.5
32	8	18.6	58.1
33	4	9.3	67.4
34	6	14.0	81.4
35	3	7.0	88.4
36	2	4.7	93.0
37	1	2.3	95.3
39	1	2.3	97.7
40	1	2.3	100.0
Total	43	100.0	

Table 4.2-5: Frequency Distribution of Total Decision Quality

4.3 Inferential Statistics

4.3.1 Cronbach Coefficient Alpha

The scale was named after American psychologist Lee Cronbach in 1951. The Cronbach's alpha measures the degree to which the questions are aligned to reflect the underlying constructs. The range of the test is between 0 and 1 with a score above 0.7 is considered acceptable. Reliability is the degree to which the results are repeatable in circumstances (Leech et al., 2014). It can be used when scale items are continuous or dichotomized. For this study, the Likert scale was used. So, the Cronbach alpha is recommended. The ranges are as follows (i) $\alpha > 0.9$ is excellent. However, some scholars argue that this is a cause for concern that this inflated value may be due to missing values, (ii) $0.8 < \alpha < 0.9$ is good, (iii) $0.7 < \alpha < 0.8$ is acceptable. However, anything below 0.7 is unacceptable.

The two assumptions for using Cronbach Alpha are (i) there is no correlation among error of items, (ii) the items are tau-equivalent (when factor loadings are assumed to be the same, all the variables are varying freely without constraint).

Table 4.3-1 - Cronbach's Alpha's table for internal consistency

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.945	0.946	24

The value of 0.945 is an excellent internal consistency of 24 scale items in the survey.

However, as noted, an internal consistency above 0.9 indicates missing data as shown in the case processing summary.

Case Processing Summary			
		N	%
Cases	Valid	36	83.7
	Excluded [a]	7	16.3
	Total	43	100.0
a. Listwise deletion based on all variables in the procedure.			

4.3.2 Correlation

Pearson's product moment correlation coefficient denoted by r, was first published by Karl Pearson in 1896 for the royal society of London (Leech et al., 2014). It represented the average set of products by equation:

$$r = \sum xy/n$$

Where

x = deviation of X scores from Mean

y = deviation of Y scores from Mean

n = Total number of Pairs

It does have some assumptions such quantitative measures (interval or ratio types), linearity with absence of outliers, normally distributed and a minimum of 30 observations.

Correlation is the strength of the extent to which two variables are related. A negative correlation means that increase in one variable leads to decrease in the other whilst a positive correlation means that both the variables increase together.

Spearman's rank correlation denoted by ρ is a non-parametric version of Pearson. The assumption of normally distribution is thus waived. The monotonic relation means that when X increases then Y may decrease or increase but not necessarily in a linear manner. If the ρ value < 0.05 is indicative of a strong correlation between variables.

Table 4.3-2: Pearson Correlation Results

Correlations						
		Information Quality	System Quality	BI Team Service Quality	BI Competency	Decision Quality
Information Quality	Pearson Correlation	1	.653**	.374*	.363*	.547**
	Sig. (2-tailed)		0.000	0.013	0.017	0.000
	N	43	43	43	43	43
System Quality	Pearson Correlation	.653**	1	.541**	.577**	.733**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000
	N	43	43	43	43	43
BI Team Service Quality	Pearson Correlation	.374*	.541**	1	.602**	.529**
	Sig. (2-tailed)	0.013	0.000		0.000	0.000
	N	43	43	43	43	43
BI Competency	Pearson Correlation	.363*	.577**	.602**	1	.627**
	Sig. (2-tailed)	0.017	0.000	0.000		0.000
	N	43	43	43	43	43
Decision Quality	Pearson Correlation	.547**	.733**	.529**	.627**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	
	N	43	43	43	43	43
****. Correlation is significant at the 0.01 level (2-tailed).**						
***. Correlation is significant at the 0.05 level (2-tailed).**						

For this study, the Pearson correlation will be used to test the various hypothesis.

Table 4.3-3: Spearman's Correlation Results

Correlations						
Spearman's rho		Information Quality	System Quality	BI Team Service Quality	BI Competency	Decision Quality
Information Quality	Correlation Coefficient	1.000	.498**	.355*	.356*	0.255
	Sig. (2-tailed)		0.001	0.020	0.019	0.099
	N	43	43	43	43	43
System Quality	Correlation Coefficient	.498**	1.000	.527**	.596**	.610**
	Sig. (2-tailed)	0.001		0.000	0.000	0.000
	N	43	43	43	43	43
BI Team Service Quality	Correlation Coefficient	.355*	.527**	1.000	.571**	.472**
	Sig. (2-tailed)	0.020	0.000		0.000	0.001
	N	43	43	43	43	43
BI Competency	Correlation Coefficient	.356*	.596**	.571**	1.000	.703**
	Sig. (2-tailed)	0.019	0.000	0.000		0.000
	N	43	43	43	43	43
Decision Quality	Correlation Coefficient	0.255	.610**	.472**	.703**	1.000
	Sig. (2-tailed)	0.099	0.000	0.001	0.000	
	N	43	43	43	43	43
****. Correlation is significant at the 0.01 level (2-tailed).**						
***. Correlation is significant at the 0.05 level (2-tailed).**						

4.3.3 Multiple Linear Regression

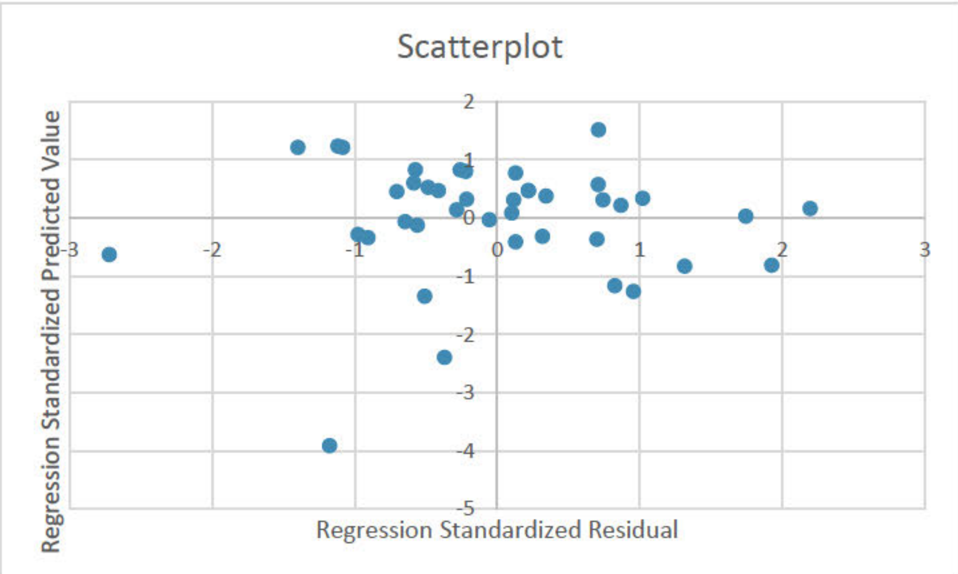
Multiple regression is when there are many independent variables that could affect a single dependant variable. This study sought to make predictions in terms of the quality of decision-making, to predict how much of variance could be explained by the independent factors namely; information quality, system quality and BI team service quality. Since previous sections showed a high correlation between the constructs, it makes sense that this study attempts a cause effect model.

$$\begin{aligned} &\textit{Decision Quality} \\ &\qquad = \beta_1(\textit{Information Quality}) + \beta_2(\textit{System Quality}) \\ &\qquad + \beta_3(\textit{Service Quality}) + \textit{Error} + \textit{Constant} \end{aligned}$$

The assumptions of linear multiple regression: (i) linearity and additivity, (ii) independence of errors or lack of autocorrelation, (iii) homoscedasticity, (iv) multivariate normality and (v) No multicollinearity (Leech et al., 2014).

The β term is known as residuals which represent some amount of error with the prediction. The assumption of lack of autocorrelation between these residuals are tested using the Durblin-Watson test in SPSS. If the Watson test value is close to two then the error term is not highly correlated. The study found the value to be 2.58, see Table 4.3-5.

The homoscedasticity assumption indicates that the error terms must be homogeneous is shown by diagram below.



The assumption of multivariate normality is the ratio of skewness and Kurtosis. If this value is greater than 1.98, then there is multivariate normality in the data. The assumption of no multicollinearity means that the predictor variables must not be so highly correlated that they are un-separable. SPSS gives us the variance inflation factor (VIF). This is a measure of whether a predictor variable has a strong correlation with other predictor variables. Some scholars agree that a value of less than 3 will mean no multicollinearity. Leech et al. (2014) prefer a value of up to 5. The VIF values are under 3. So, the assumption is accepted (see below), a tolerance value greater than 0.1, all our tolerances comply.

Table 4.3-4 - Multicollinearity test

Coefficients [a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	7.442	3.237		2.299	0.027		
	Information Quality	0.227	0.232	0.123	0.977	0.335	0.580	1.724
	System Quality	0.953	0.238	0.577	4.013	0.000	0.448	2.231
	BI Team Service Quality	0.335	0.182	0.218	1.835	0.075	0.655	1.528
a. Dependent Variable: Decision Quality								

The enter method was used. It is the most popular and it assumes that all the variables are of equal importance.

Table 4.3-5 - Multiple Regression Summary

Model Summary [b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.811[a]	0.657	0.629	3.182	2.581
a. Predictors: (Constant), BI Team Service Quality, Information Quality, System Quality					
b. Dependent Variable: Decision Quality					

Correlation denoted by R measures the strength of the relationship. It does not guarantee the cause and effect relationship, but is a necessary condition for it. The R value is 0.811 is significant.

R square is the percentage of influence explained by the independent variables (information quality, system quality, BI team service quality) in the dependant variable (decision quality). This means that only 65.7% of the decision quality can be explained or accounted by information quality, system quality and BI team service quality.

Table 4.3-6 - ANOVA

ANOVA [a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	718.227	3	239.409	23.644	.000[b]
	Residual	374.651	37	10.126		
	Total	1092.878	40			
a. Dependent Variable: Decision Quality						
b. Predictors: (Constant), BI Team Service Quality, Information Quality, System Quality						

Whilst the ANOVA is significant, the R Squared does not explain above 80% of the decision quality, we cannot determine a sufficient cause effect model, despite the high correlation.

4.3.4 Hypothesis Testing

The null hypothesis was:

H0 – Information quality, System quality and BI Service Quality has no influence on the quality of decision making

The three-research hypothesis are

I. H_1 - Information Quality has a positive impact on the quality of decision-making using BI
II. H_2 - System Quality has a positive impact on the quality of decision-making using BI
III. H_3 - BI Service Quality has a positive impact on the quality of decision-making using BI

The Pearson's correlation in Table 4.3-2 shows significant correlations, denoted by * or ** between the variables.

H_1 – information quality was found to have a strong positive significant relationship to decision quality with a correlation value of .547** at the 99% interval.

H_2 – system quality was found to have a strong positive significant relationship to decision quality with a correlation value of .733** at the 99% interval. This was the strongest relationship of the three constructs.

H_3 – BI team service quality was found to have a strong positive significant relationship to decision quality with a correlation value of .529** at the 99% interval. This was the weakest relationship of the three constructs.

Since all three hypothesis H_1, H_2, H_3 were found to have a positive significant, the null hypothesis is not valid. Therefore, the study rejects the null hypothesis and concludes that information quality, system quality and BI team service quality positively influences the quality of decision-making. This relationship stood at the 99% level.

4.4 Chapter Summary

This chapter analysed the results from the survey using both descriptive and inferential statistics. It found that there was a positive relationship between all dependant variables namely; information quality, system quality and BI team service quality with the quality of decision making. Due to a high correlation value, the study further analysed a cause effect linear regression on the three dependant variables. It found that there was a significant relationship between the dependant variables and that 65.7% of the participants indicated the influence of BI on decision-making quality. It was also found that this could be explained by the three variables.

The next chapter concludes the study.

CHAPTER FIVE: DISCUSSION, CONCLUSIONS & RECOMMENDATIONS

5.1 Introduction

This chapter concludes the study as a whole. It revisits the main areas which are information quality, system quality and BI team service quality on the quality of decision making. It also highlights the research hypothesis and objectives in line with the findings and offers recommendations to make the organisational BI implementation more successful.

The study aimed to answer four research objectives:

I. To investigate the factors influencing the quality of decision-making using business intelligence in Hulamin-KZN;
II. To determine if information quality has a positive impact on the quality of decision-making using business intelligence in Hulamin-KZN;
III. To determine if system quality has a positive impact on the quality of decision-making using business intelligence in Hulamin-KZN; and
IV. To determine if BI service quality has a positive impact on the quality of decision-making using business intelligence in Hulamin-KZN.

The three null hypotheses were:

I. H_0 - Information quality has no influence on the quality of decision-making using BI.
II. H_0 - System quality has no influence on the quality of decision-making using BI.
III. H_0 - BI service quality has no influence on the quality of decision-making using BI.

The three-research hypothesis are:

I. H_1 Information Quality has a positive impact on the quality of decision-making using BI.
II. H_2 System Quality has a positive impact on the quality of decision-making using BI.
III. H_3 BI Service Quality has a positive impact on the quality of decision-making using BI.

Chapter four presented the results from the self-administrated questionnaire. Descriptive statistics covered areas such as the demographics whilst inferential statistics went through the analysis techniques and highlighted significant findings and tested various hypothesis. Chapter five concludes the study by revisiting the research objectives. It also presents major findings both from the literature as well as from the primary survey.

The Pearson's correlation highlighted that there was a strong correlation between the various themes and decision-making quality using BI. These included information quality, system quality and BI service quality. A strong positive correlation of 0.547 existed between information quality and decision quality. This is consistent with literature findings whereby high-quality information lead to high quality decision-making.

The second finding is that there is a strong positive correlation between system quality and decision quality. A value of 0.733 was also consistent with literature findings whereby a good infrastructure and ease of use leads to better decision-making. Results show that this was the strongest relationship among the three variables.

The third finding is that BI service quality is positively correlated to decision quality with a Pearson correlation value of 0.529. This also is consistent with literature in that analytical skills and domain knowledge coupled with strong BI management leads to better quality decisions and facilitates organisational learning. This is an important contribution to the firm's competitiveness when viewed from the resource-based view as the collaboration between analysts and decision-making and the interaction with the BI assets is unique and difficult to copy.

Other findings show that whilst all information quality, system quality and BI service quality all are significantly positively with BI competency, BI service quality has the strongest influence. This is consistent with literature, as the firm's resources and collaboration influence the firm's capability.

Further, inferential analysis was conducted to measure how strong the influence of the three variables under study were. In order to decide quality, a multiple linear regression revealed that the three variables could explain 65.7% of the variance in the decision-making quality.

5.2 Demographic Data

The study sample constituted 53% non-managers and 47% managers. The percentage of managers who used BI reports daily was 17.5%. Those who used BI few times a week constituted a total of 17.5% and while those who used it only a few times were about 10%. The percentage of non-managers who used the reporting system daily was 35%. This was followed by few times a week (7.5%) and a few times a month at 5%.

The majority of participants (30%) had less than 2 years of BI experience. This was followed by those with 2 - 4 years of BI experience (25%). A total of about 22.5% had more than 10 years of experience.

5.3 Constructs

5.3.1 Objective 1 – To determine the influencing factors on decision making quality

5.3.1.1 Findings from study

There was a positive significant correlation between dependant variables on information quality, system quality and BI service quality with independent variable decision quality. The study used Pearson's correlation and the result was at the 99% interval. Further, analysis was done using multiple linear regression to find the strength of the three variables on the influence of decision-making. It was found that the three variables explained 65.7% of the variance in the decision-making quality.

5.3.1.2 Significant observations from literature

A situation whereby a decision is required under pressure and faced with constraints such as limited time, limited knowledge, and limited processing capability is referred to as the bounded rationality problem (Simon, 1991). The study found that information quality had a positive significant impact on decision makers processing capability (Kowalczyk and Gerlach, 2015). This is consistent with the findings of the study whereby there was a strong positive correlation between information quality and decision quality.

Ghasemaghaei et al. (2018) argue that firm resources play a critical role in ensuring that BI leads to improved organisational decision-making. This is consistent with the findings of the study with strong positive correlation between BI service quality and decision-making quality.

System quality contributes to better decision-making and net benefits to the organisation (Delone and McLean, 2003, Wixom and Watson, 2001). This is consistent with the findings in the study whereby there was a positive strong correlation between system quality and decision-making quality.

5.3.2 Objective 2 – To determine if either information quality positively affected decision-making quality or had no effect

5.3.2.1 Findings from study

The following findings were established from questions related to information quality as a possible factor that influenced the quality of decision-making. An overwhelming majority of the participants (72.5%) agreed that information quality was perceived as high quality. Only About 2.5% disagreed and the remainder was neutral. A significant positive correlation was established between information quality and the quality of decision-making using Pearson's correlation technique. This was consistent with various previous studies (Popovič, Hackney, Coelho and Jaklič, 2012, Adrian et al., 2018, Wieder and Ossimitz, 2015, Visinescu et al., 2017). The other significant finding was the strong correlation between information quality and BI service quality, and BI competency. It found that a significant Pearson correlation value of 0.374 between information quality and BI service quality meant that high quality information improves BI service delivery. This means that users can trust the data. The study revealed that there was a positive strong correlation between information quality and system quality. A Pearson correlation value of 0.653 implied that having high quality information would improve the overall system quality perception.

5.3.2.2 Significant observations from literature

There is vast body of literature on improving data quality mechanisms and methodologies. Wang and Strong (1996) argued that firms must put in effort to ensure that data quality is equal to the effort of ensuring product quality. They introduced a framework based on total quality management principles called total data quality management (TDQM). This is now known as master data management. A study by (Kowalczyk and Gerlach, 2015) found that information quality had a positive impact on decision-makers' processing capability.

An interesting result was that 7.9% of the participants disagreed that the information was up to date. This was the highest percentage for disagreement among all the four questions related to information quality. This highlights the problem of data staleness in literature. This was consistent with a study of six companies that experienced issues stemming from poor data, due to not having a master data management strategy. There is a variety of techniques to monitor the quality of the data during the lifecycle. It must take into cognisance the time, scope and frequency of measurement, large organisations take master data management seriously and have dedicated departments and data governance strategies in place to ensure data quality (Otto, 2015).

5.3.3 Objective 3 – To determine if either system quality positively affected decision-making quality or had no effect

5.3.3.1 Findings from study

The Pearson correlation value between system quality and decision quality was positively (0.733) which was significant in the 99% confidence range. This was the highest correlation between all three variables of the study. The measurements that were used for this category included (i) ease of system use, (ii) system accessibility (iii) system accuracy and (iv) ease of learning. The results showed that 83% found the system easy to use, 78.1% found the system very accessible, 75.6% found the system easy to learn. System quality also has a positive significant correlation with BI competency, with a Pearson correlation value of 0.577. This implies that a high-quality system would increase the BI capabilities of the organisation. System quality was also strongly positively related to BI Service quality implying that having a high quality BI system could result in better quality service from the BI department since the system is easy to use and learn, accurate and accessible.

5.3.3.2 Significant observations from literature

The findings of the study are consistent with the literature review which revealed that system quality contributes to better decision-making and net benefits to the organisation (Delone and McLean, 2003, Wixom and Watson, 2001). BI infrastructure was significantly correlated to Operational BI capabilities and positively correlated to Strategic BI capabilities (Fink et al., 2017).

5.3.4 Objective 4 – To determine if either BI team service quality positively affected decision-making quality or had no effect

5.3.4.1 Findings from study

A significant positive Pearson correlation value of 0.529 was found between BI service quality and decision quality. This meant that good BI service and high-quality decision-making move upward together. This aligns with findings from literature.

Another finding was a significant positive correlation of 0.602 was found between BI team service quality and BI Competency, a significant positive correlation of 0.541 was also found between BI team service and system quality.

A third finding was significant at 95% and had a positive correlation of 0.374 that was between BI service quality and information quality.

5.3.4.2 Significant observations from literature

Ghasemaghaei et al. (2018), argue that firm resources play a critical role in ensuring that BI leads to improved organisational decision-making. A quantitative survey administrated to 500 Australian public companies regarding questions on BI management, data and information quality, BI scope and decision-making quality revealed that BI management positively affected the quality of decision making (Wieder and Ossimitz, 2015). This is consistent with the findings from the study with high correlation between BI service quality and decision-making quality.

A positive significant correlation was found between BI team service, mediated by BI infrastructure to BI capabilities (Fink et al., 2017). This was consistent with the findings of the study since both a positive significant relationship between BI team service quality and BI competency as well for system quality. This is consistent with the finding from the study with a strong positive correlation between BI service quality and BI competency and lastly decision-making quality.

Effective BI management results in good quality information. This finding is consistent with reviewed literature (Chae, Yang, Olson and Sheu, 2014, Li and Joshi, 2012, Ghasemaghaei et al., 2018). This is also consistent with the study finding. However, the strength is not as strong compared to the other correlations found as this was for the 95% range whilst others were for the 99% interval.

5.4 Recommendations

The results of this study are encouraging to senior managers as it indicates that the organisation exhibits a high level of decision-making quality. However, as noted by Davenport and Harris (2017), the transition to becoming a data-driven (fact-based decision making) organisation using advanced analytics could enable the organisation to become a global competitor in terms of information utilisation.

Chae et al. (2014) used survey data from global manufacturing research group and applied structural equational modelling, it suggests that for manufacturing companies to take advantage of advanced analytics such as optimisation techniques in the supply chain, they must be used in conjunction with initiatives such total quality management just in time together with statistical process control in order to ensure a high quality of accurate data.

The recommendation for Hulamin is to:

- Improve information quality especially protection from staleness by incorporating a master data strategy into the IT strategy. This strategy must focus on governance of data lifecycle and data quality measuring and improvement mechanisms. It must monitor the quality of data and report on it just as other initiatives such the visual management project.
- Seek infrastructure opportunities using cloud-based offering. Benefits could include improvement of collaboration between customers and suppliers, lower operational costs, better security with more updates and increased scalability (Balco, Law and Drahošová, 2017).
- Seek opportunities of Big data analytics with cloud computing leads to many benefits with improved data mining abilities and advanced analytics support. It is quite luring for companies which have not yet the infrastructure or capability and seeking to exploit the opportunity (Balachandran and Prasad, 2017).
- Focus on ensuring good technical skills (analysis and programming) and good managerial skills (communications and domain knowledge) by offering training and fostering a culture that supports collaboration. Studies on a centralised BI department have shown that it has the autonomy to hire skilled analysts like data scientists which fills the gap between technical and business knowledge (Davenport and Harris, 2007). Therefore, the recommendation is that the organisation under study put in place some plans and a structure to attract, retain and improve people with technical and analytical skills.

Moyo and Loock (2016) reviewed 39 studies on South African companies using cloud-based technologies and found that the two main challenges to cloud adoption are security threats, followed by mistrust in cloud service providers.

5.5 Limitations of the study

The scope of this research was limited to one aluminium rolling plant in KwaZulu-Natal. It is therefore not representative of the metals industry or manufacturing sector of the country. Furthermore, the research was restricted to just two sites in KZN and not the sites outside the province for the company. The study should be duplicated in other manufacturing sectors with larger sample sizes for a more generalised finding. The current sample is very small and larger trials are merited.

The research involved managers and non-managers - mostly knowledge workers - who have access to BI reporting platform. They encompass a large variety of BI experience ranging from less than 2 years to over decades of BI experience, and differ in frequency of use. The research covered four main themes namely information quality, system quality, BI team service quality and how it influences the quality of decision making all through the use of BI. The study used a minimum threshold which was determined by the number of runs to qualify. The response rate was 64.1%. The reader must exercise caution against extending these results to a broader setting.

The survey instrument was conducted in English and could be biased to English speaking participants. An enhancement would be to render the survey in a language of choice.

Finally, due to constraints on time and resources, the depth nor breath of the study may not have been covered to the author’s content. Further investigations are warranted.

5.6 Recommendations for further Research

The following recommendations are made for future research on this subject:

Decision quality using BI in the current study was measured using employee perception on the construct. Future studies can measure decision quality using organisational performance over time. Key metrics such as market share, operating profit and volume sales can be used to measure the performance of the organisation in relation to decision quality. This can be correlated with BI usage statistics.

This study was conducted in one manufacturing organisation across just two sites, within limited time and resources. Future studies of this nature may need to include sites of the organisation and extended to other manufacturers.

5.7 Summary of Chapter

Chapter four presented the results from the survey using both descriptive and inferential statistics, whilst this chapter related the findings to that of literature and recommendations to the organisation under study. It also reviewed the research objectives and rejected the null hypothesis because of the strong positive correlations of the alternative hypothesis. It explained the limitations of the study namely been constrained to a single organisation and just a cross sectional sample, there is warning that the results not be generalized to other industries. Recommendations for further research with more companies and larger sample sizes were suggested. Lastly the conclusion, which recapped the study, findings and provided general recommendations to Hulamin.

CHAPTER SIX: APPENDICES

Appendix 1: Informed consent to participate in research

Informed Consent Letter 3C

UNIVERSITY OF KWAZULU-NATAL

GRADUATE SCHOOL OF BUSINESS AND LEADERSHIP

Dear Respondent,

MBA Research Project

Researcher: Annesh Singh 087-285-7050

Supervisor: Dr. Bibi Zaheenah Chummun 031-260 8943

Research Office: Ms P Ximba 031-2603587

I, Annesh Singh an MBA student, at the Graduate School of Business and Leadership, of the University of KwaZulu Natal. You are invited to participate in a research project entitled:

Factors influencing the quality of decision making using business intelligence in Hulamin-KZN

The aim of this study is to establish the relationship between the quality of decision making using business intelligence (BI) and:

- Information quality
- System quality
- Service quality

Through your participation I hope to understand the role and impact of these key variables on the quality of decision making. The results of the survey are intended to contribute to the limited academic business intelligence implementation theory and serve as a guide for BI practitioners.

Your participation in this project is voluntary. You may refuse to participate or withdraw from the project at any time with no negative consequence. There will be no monetary gain from participating in this survey. Confidentiality and anonymity of records identifying you as a participant will be maintained by the Graduate School of Business and Leadership, UKZN.

If you have any questions or concerns about completing the questionnaire or about participating in this study, you may contact me or my supervisor at the numbers listed above.

The survey should take you about 20 minutes to complete. I hope you will take the time to complete this survey.

Since this is online survey, by completing the questionnaire, you are consenting to take part in the study.

Sincerely

Investigator's signature_________________________________ Date_______________

Appendix 2 Questionnaire

Questionnaire

The following questionnaire is designed to analyse and measure the factors influencing the quality of decision making using business intelligence in Hulamin. The information gathered through this questionnaire will be kept confidential, your anonymity will be ensured and responses will only be used for research purposes. Please try to answer all questions by selecting the option that best matches your response.

Section One: Basic Data

1. Are you a manager (i.e. do you have other staff reporting to you)?
    a. Yes
    b. No
2. How many years of experience do you have in using Business Intelligence (BI) reporting (in current and previous organisations)?
    a. less than 2 years
    b. 2-4 years
    c. 5-7 years
    d. 8-10 years
    e. More than 10 years
3. How often do you use Business Intelligence reports?
    a. Once or twice a year
    b. Less than once a month
    c. A few times a month
    d. A few times a week
    e. Every day

Section Two: What factors influence Business Intelligence reports usage in Hulamin?

Please use the following ratings to indicate your response to each statement in the questionnaire:

1. *Strongly disagree*
2. *Disagree*
3. *Neither agrees nor disagrees (Neutral)*
4. *Agree*
5. *Strongly agree*

The questions you will be asked are grouped into six categories. The purpose of each of these sections is explained below:

- **Information Quality** – how up to date, accurate and reliable is the data on the BI reports, and is information in one report consistent with information provided in other similar reports
- **System Quality** – visually, are the BI reports well thought out and do they present the information in a consistent, easy to understand manner. Are the BI reports easy to use and is it easy to find the reports that you need
- **Decision Quality** – are the BI reports useful to you and do they help you to make better business decisions
- **BI Service Quality** –do you feel that the BI team are competent to understand your information requirements, and is the quality of the service provided by the BI team what you would expect?
- **BI Competency -** do you feel that the current BI processes, toolsets and adoption is mature?

Research Questions	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
Information Quality					
The information contained in the BI reports is generally up to date					
The information contained in the BI reports is accurate and reliable					
Information provided in one BI report generally agrees with that provided in similar reports					
Information provided at a summary level tallies with that provided at a more detailed level					
System Quality					
The BI reports are well designed and present the information in a clear, easy to understand manner					
The BI system is easily accessible to me					
The names of the BI reports clearly describe their purpose					
The reports are logically grouped on the reports menu					
BI Service Quality					
I find our BI team is available for assistance, support and queries					
I find our BI team is courteous and treats me with respect					
The BI team generally responds quickly to my requests					
I find our BI team tries to fully understand my problem before developing any reports					
BI Competency					

I feel that the current BI processes work very well					
I feel that the current toolset for BI work very well					
I feel that I have adopted BI to its full potential					
I plan to continue to use the BI reports in the future					
Decision Quality					
I can usually find a report that provides me with the information I am looking for					
I find that the BI reports are flexible and allow me to retrieve the information I need in an appropriate way					
Using the BI reports enables me to make decisions more quickly					
Using the BI reports enables me to make better business decisions					
Using the BI reports increases my business productivity					
I consider my usage of the BI reports to be beneficial to Hulamin					
Using BI reports has brought to light new information/insights which were previously not evident					
BI is fully integrated into my existing business processes					

Appendix 3 Gatekeeper Letter

HULAMIN

Date: 13 August 2018

Dear Mr. A Singh, (UKZN - 200270749)

Approval of research

The research proposal titled "*Analyse and measure factors influencing business information and analytics (BIA) use in Hulamin*" was reviewed by Hulamin, and is hereby **approved,** for research to be undertaken at Hulamin premises.

You are requested to take note of the following:

1. Confidentiality of Hulamin process information, including staff and customer information, must be maintained at all times;
2. You are to ensure that your data collection process will not interfere with the routine tasks of the factory;
3. Informed consent is to be obtained from all participants in your study, if applicable;
4. Policies, guidelines, safety processes and protocols of Hulamin must be adhered to at all times;
5. Professional attitude and behaviour whilst dealing with research participants must be exhibited;
6. Hulamin and its staff will not be held responsible for any negative incidents and/or consequences, including injuries that may be sustained on site or litigation matters etc. that may arise as a result of your study or your presence on site;
7. You are requested to work with Colin Steijl (BI Manager) once you are ready to commence data collection.

Recommended By:

[redacted]

Colin Steijl [redacted]
BI Manager

Approved By:

[redacted]

Doug Seager
Senior IT Manager

Hulamin Limited | Registration No 1940/013924/06
Moses Mabhida Road, Pietermaritzburg, 3201 | PO Box 74, Pietermaritzburg, 3200, South Africa
Tel: +27 (0)33 395 6911 | **Fax:** +27 (0) 33 394 6335| **Email:** hulamin@hulamin.co.za | **Website:** www.hulamin.co.za
Directors: T P Leeuw (Chairman), RG Jacob (Chief Executive Officer), CA Boles, VN Khumalo, AP Krull, RL Larson,
N Maharajh, NNA Matyumza, Dr. B Mehlomakulu, MZ Mkhize, SP Ngwenya, PH Staude, GHM Watson | **Secretary:** W Fitchat

Appendix 4 Ethical clearance

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

23 October 2018

Mr Annesh Singh (200270749)
Graduate School of Business & Leadership
Westville Campus

Dear Mr Singh,

Protocol reference number: HSS/1699/018M
Project title: Factors influencing the quality of decision making using business intelligence in Hulamin-KZN

Approval Notification – Expedited Application

In response to your application received 25 September 2018, the Humanities & Social Sciences Research Ethics Committee has considered the abovementioned application and the protocol has been granted **FULL APPROVAL.**

Any alteration/s to the approved research protocol i.e. Questionnaire/Interview Schedule, Informed Consent Form, Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through the amendment /modification prior to its implementation. In case you have further queries, please quote the above reference number.

PLEASE NOTE: Research data should be securely stored in the discipline/department for a period of 5 years.

The ethical clearance certificate is only valid for a period of 3 years from the date of issue. Thereafter Recertification must be applied for on an annual basis.

I take this opportunity of wishing you everything of the best with your study.

Yours faithfully

[redacted]

Professor Shenuka Singh (Chair)

/ms

Cc Supervisor: Dr Bibi Zaheenah Chummun
Cc Academic Leader Research: Professor Muhammad Hoque
Cc School Administrator: Ms Zarina Bullyraj

Humanities & Social Sciences Research Ethics Committee
Professor Shenuka Singh (Chair)
Westville Campus, Govan Mbeki Building
Postal Address: Private Bag X54001, Durban 4000
Telephone: +27 (0) 31 260 3587/8350/4557 **Facsimile:** +27 (0) 31 260 4609 **Email:** ximbap@ukzn.ac.za / snymanm@ukzn.ac.za / mohunp@ukzn.ac.za
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Appendix 5 Turnitin Report

Turnitin Originality Report

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200270749 MBA Thesis Final By Annesh Singh

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In Lih Ong, Pei Hwa Siew. "chapter 12 Empirical Investigation on the Evolution of BI Maturity in Malaysian Organizations", IGI Global, 2015

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Karlinsky-Shichor, Yael, and Moshe Zviran. "Factors Influencing Perceived Benefits and User Satisfaction in Knowledge Management Systems", Information Systems Management, 2015.

< 1% match (student papers from 02-Feb-2015)
Submitted to Grenoble Ecole Management on 2015-02-02

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