

Factors Influencing the Quality of Decision-Making Using Business Intelligence in a Metal Rolling Plant in KwaZulu-Natal

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Abstract: The current study sought to investigate the factors which influence the quality of decision-making using business intelligence (BI) in a metal rolling plant in KwaZulu-Natal. Specifically, the study was focused on information quality, system quality and BI service quality. The study used a self-administered survey sent out to participants having sufficient report runs which made up 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, and the data was imported into SPSS for analysis. The results 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 quality had a positive significant impact on the quality of decision-making. Multiple linear regression analysis was conducted to determine the strength of these variances in influencing decision-making. It was found 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. The study recommends that the company implement data quality management focusing on data cleansing, it should also implement more sophisticated analysis techniques to get insights and have strategies to upskill both technical and business workers.

Keywords: Business Analytics, Business Intelligence, Information Quality, System Quality, Service Quality, Quality of Decision Making.

1. INTRODUCTION

Competition in the 21st century is intense with most competitor companies now 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 needed to compete in a dynamic environment (Davenport & Harris 2017).

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 & Yeoh 2009; Negash 2004; Vinaja 2016; Watson 2009). According to Gartner (2017), the BI and analytics market is becoming increasingly central and by the year 2020 yield a market share of \$22.8 billion. It is not well understood how a BI investment creates business value (Krishnamoorthi & Mathew 2018). The partial causal relationship between information systems (such as BI) investments and business value remains unconfirmed, and this is believed to be an ongoing subject of research for information system researchers (Schryen 2013).

There is a belief that managerial experience combined with BI tools could increase the quality of decisions in organisations. However, a study on the reasons for BI failure found that poor data quality, insufficient business involvement, poor system design and reluctance of users to change from old tools such as spreadsheets are some of the causes of failure in BI implementation (Lupu, Bologa, Lungu & Bra 2007). A survey on key challenges for big data implementation found similar reasons for failure. The most prevalent in this survey was the challenge of scattered data across various departments (Colas, Finck, Buvat, Nambiar & Singh 2014). A mixed methods study of 43 managers in large organisations found that the BI implementations failed to support effective decision-making for similar reasons (Riabacke, Larsson & Danielson 2014). In addition, it was found that the most common reason was that the BI implementation was treated as another information system implementation focusing on technical needs without understanding the decision-makers' requirements. A recent report by the McKinsey Global Institute which used survey data collected from several United States of America (USA) company executives showed that companies only harnessed a fraction of their data and analytics value (Henke *et al.* 2016) due to the limited analytical capability of these organisations. This finding is supported by Meulen and McCall (2018) which surveyed 196 organisations worldwide and found that 60% are still in the lowest maturity levels. The primary

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objective of this study is to investigate the factors influencing the quality of decision-making using business intelligence in a metal rolling plant in KwaZulu-Natal.

2. OBJECTIVES OF THE PAPER

The objectives are as follows:

2.1. Primary Objective

To investigate the factors influencing the quality of decision-making using business intelligence in a metal rolling plant in KwaZulu-Natal.

2.2. Secondary Objectives

- To determine if information quality has a positive impact on the quality of decision-making using business intelligence in a metal rolling plant in KwaZulu-Natal.
- To determine if system quality has a positive impact on the quality of decision-making using business intelligence in metal rolling plant in KwaZulu-Natal.
- To determine if BI service quality has a positive impact on the quality of decision-making using business intelligence in a metal rolling plant in KwaZulu-Natal.

3. PROBLEM STATEMENT

Organisations have a burden to create value which will eventually result in financial gain for all the actors (Thulani, Chitakunye & Chummun 2014). 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 & Davern 2008; Jourdan, Rainer & Marshall 2008). A recent survey of 226 executives across Europe and North America show that only 27% reported their business intelligence initiatives as successful (Colas *et al.* 2014). One of the leading challenges that BI implementations face is ensuring that high quality information is transferred into outputs of BI assets for decision-making. There is a lack of research showing how business intelligence could be used to improve the quality of decision making in organisations (Cao, Duan & Li 2015; Janssen, van der Voort & Wahyudi 2017). The available literature on BI success also overlooks the potential of BI in improving decision-making quality. Thus, our understanding in how decision-making could be improved by BI remains

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

The business value of the BI investment in the manufacturing plant under study has not been measured 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.

4. FACTORS INFLUENCING THE QUALITY OF DECISION-MAKING

A decision is defined as the irreversible outcome of committing resources (human resources, capital, material, time) to a choice between several alternatives (Abbas & Howard 2015). Delen, Moscato and Toma (2018) explains that that in practice, decision-making in most organisations is done in a non-rational way. This is referred to as 'gut feel' decision-making. It is also known as the bounded rationality constraints problem whereby parameters such as time or knowledge are limited (Riabacke *et al.* 2014). Goldoff (2000) explains that Kiel's third principle of chaos implies that an unusual event has the potential to change an entire system, and the unwillingness of managers to adapt, but rather stick to the status quo leaves the whole organisation suffering.

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). Decision quality is ultimately a function of effectiveness and efficiencies in the decision-making process. 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, Jones & Sidorova 2017).

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). Maturity theories explain how an organisation progresses from making decisions intuitively to becoming a data-driven or an analytical organisation, it moves from silo to a holistic organisational BI view (Davenport & Harris 2017; Olszak 2016; Popovič, Hackney, Coelho & Jaklič 2012). A recent BI maturity

survey done across Europe, the Middle East and Africa showed that only 30% of organisations within reached the top two maturity levels - differentiating or transformational (Meulen & McCall 2018). The report further explained that technology was not the issue. It revealed that the three biggest barriers were how to define the BI strategy, determining how to measure value from BI initiative and solving risk and governance issues.

Organisational-level benefits of BI are difficult to measure since many factors are continuously operative in the organisation. It is difficult to isolate BI as a factor from the other factors that are also operative in the organisation. In addition, for most organisations that have not implemented a big bang approach of BI, there might be pockets of successful BI implementations at departmental level, thereby making it difficult to gauge the overall net effect of BI (Wixom & Watson 2001). Agile BI helps to realise the return on investment sooner as decision-makers can get value quicker. This dynamic way of working helps the business to evolve and adapt to changes quicker (Wazurkar, Bhadoria & Bajpai 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). Firms that are successful will effectively use BI within their business processes to create unique capabilities. This could also have a positive impact on the organisation. For instance, Chummun (2018) put forward how artificial intelligence which forms part of the business intelligence counteracts fraud in the inclusive cover niche in the developing countries. However, it has been noted that there are very little studies understanding how BI systems may be effectively used to create a positive impact (Côrte-Real, Ruivo & Oliveira 2014).

An information culture refers to shared beliefs, attitudes and values of the employees within a single organisation (Chummun & Gaffar 2018). Power (2016) explains that a company's information culture can be one of the 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, influences 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 experiences 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) concluded in their study that firms that were more successful were those that had a higher analytical culture which they used as the main driver in analytical decision-making. Ghasemaghahi, Ebrahimi and Hassanein (2018) argue that firm resources play a critical role in ensuring that BI leads to improved organisational decision-making. The resource-based view suggests that the qualities and arrangement of resources makes the firm distinct from a competitive perspective. Resources must be valuable, inimitable and non-substitutable (Ji-fan Ren, Fosso Wamba, Akter, Dubey & 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 & Harris 2017). Data driven analytical firms include the Amazon which harnessed big data to disrupt the conventional book industry and become a leader in online shopping. Google also exploited data from its search engine to provide personalised advertising based on individuals preferences. Facebook also used personalised 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 & Kopanakis 2018).

A study by Janssen *et al.* (2017) in the Dutch revenue collection organisation found that several factors influenced decision-making quality. These included analytical tools and analytical capabilities, and process integration and standardisation which results in lower efforts. Experience of decision makers leads to faster decisions, communication and knowledge exchange between analysts and decision makers.

Another study by (Ghasemaghahi *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 1) found that all factors positively affected the quality of decision making in organisations.

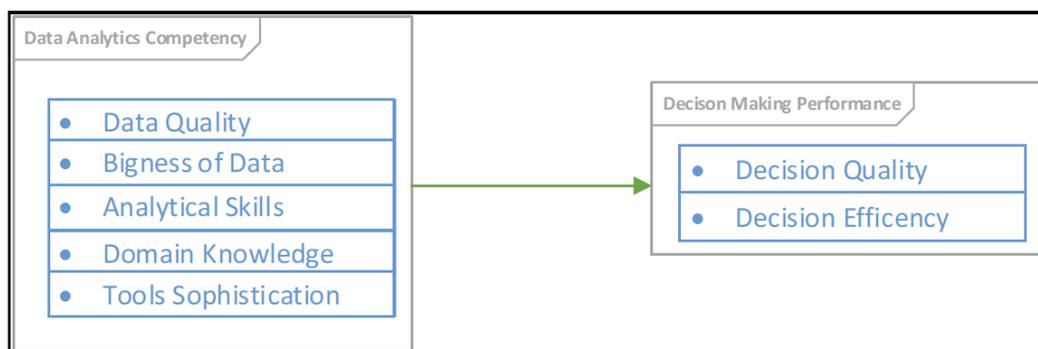


Figure 1: BI impact on decision making performance – adapted (Ghasemaghaei *et al.* 2018).

Visinescu *et al.* (2017) conducted a study on 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. Survey data was collected from 61 BI users across several industries in US and found that these factors had a positive relationship to perceived decision quality using BI.

Adrian, Abdullah, Atan and Jusoh (2018) proposed a model consisting of three dimensions namely; the organisational, the people and the technology in order to have an effective decision making process.

4.1. Information Quality

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 & Ossimitz 2015). A study on six large organisations showed that the master data was a strategic asset which added to the competitive capability of the firm with regard to the resource based view (Otto 2015). Data entry problems such as misspelling, lack of input validation, incorrect formats and syntaxes reduce the quality of data (Eckerson 2002). Data quality remains the most cited 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 & 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 & Strong 1996). It is the information product (typically reporting); and includes measurements such as information accuracy, relevance, recentness, credibility, timeliness and importance (DeLone & McLean 1992). 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, Ossimitz & Chamoni 2012). High data quality does not always translate 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 & Ossimitz 2015; Wixom & Watson 2001).

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 & Joshi 2012). 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). Raghunathan (1999) 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. Li and Joshi (2012) were some of the first researchers to investigate the cost/benefit analysis of data cleansing mechanisms. They found several challenges, but concluded that data cleansing efforts were often a worth the investment. 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 suggested that a continuous improvement approach is required to the maintenance and assessment of the quality of data

Wang (1998) argued that firms must put some effort to ensure data quality in as much as they work towards ensuring product quality. Wang (1998) suggested that a continuous improvement approach is required such as the total data quality management (TDQM). An extension to the TDQM added a weighting to data because some data are more strategically important than others (Vaziri, Mohsenzadeh & Habibi 2017).

4.2. 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 & McLean 1992).

The updated information system model included a few more measures for the system quality construct including reliability, ease-of-use, functionality, portability and importance (Delone & 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 & Ossimitz 2015).

(Nelson & 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. The five constructs to define system quality in their model were (i) reliability, (ii) flexibility, (iii) accessibility, (iv) response time; and (v) integration.

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 can recover from 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 and 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 & 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 was 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.

4.3. 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 & McLean 2003; Karlinsky-Shichor & Zviran 2016). In an information systems adoption context, there is an argument that service quality is not significant to perceived benefits (Venkatesh, Morris, Davis & Davis 2003). However, in the area of knowledge management systems, it was found that service quality was a significant influencing factor (Karlinsky-Shichor & 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 & Ossimitz 2015). A study using 62 managers found that managerial involvement in the adoption process had a significant positive relationship to adoption intension (Wang 2014). 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 & Koronios 2010; Yeoh & 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. A study using 500 Australian companies found that BI management positively affected the quality of decision-making (Wieder & 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. This elaborate task is the responsibility of the BI team. 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 & Buxmann 2015).

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, neural nets, simulation and optimisation results are intimidating to business decision-makers. Thus, they require strong collaboration with analysts in the interpretation and advise on the choice of action based on the product. The gap between the analysts and business decision-makers is heightened by the business expert's lack of advanced analytics knowledge. This may further be worsened the analyst's lack of business knowledge (Janssen *et al.* 2017).

The role of the analysts in influencing the decisions is paramount when using complex analytics processing

methods. A study using data from 136 decisions using BI revealed that high levels analytics reduced the quality of heuristic making decisions whilst the collaboration of analysts significantly increased the quality of systematic making decisions (Kowalczyk & Gerlach 2015).

4.4. Decision-Making and Business Value

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 & Hulland 2004). However, 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; and thus, distinguish the company from its competitors (Fink, Yogev & Even 2017). BI value when viewed under the lens of learning and innovation means 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). A survey study by Torres, Sidorova and Jones (2018) found a positive relationship between business analytics and the firm's performance which was mediated by the dynamic capability of the firm to utilize BI whilst sensing and seizing opportunities.

Sharma, Mithas and Kankanhalli (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 resource-based view (RBV) theory (see Figure 2 below).

The first stage is data to insight. It must be noted that insight is not merely the results after analysis of the BI system, but rather insights emerge out of engagement between analysts and decision-makers. These engagements would require a change to the organisational structure to support and facilitate this engagement between analysts and business managers



Figure 2: Data insight decision value flow – source: adapted from (Sharma *et al.* 2014).

(Kowalczyk & 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 used as advanced analytics to understand patterns and relationships of the data; and automation 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, but 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) show that it is difficult for the central unit to convert their insights into value because of competitive actions by business units. Decision-making using BI reports relied on experience of the user and ability to create insights (Riabacke *et al.* 2014).

The second stage is converting insights to decisions. There is not usually a one-to-one mapping from insight into decision-making since 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 the debate to convert the various insights into the best decision for the desired goal; and hence, the competitive advantage is dawned (Frisk, Lindgren & Mathiassen 2014). Insights into a decision is not obvious and easily automated.

Consider the case study whereby UPS implemented an analytical programme called Orion (On-road integrated optimisation and navigation) which saved 100 million miles by minimising on left turns by using alternative routes (Davenport & Harris 2017). However, the decision from the insight was to outsource those routes. This was not an obvious decision, but it yielded maximum returns for UPS; thus, serves as an example of how insights and collaboration between decision-makers lead to a successful implementation for the company and yield reduced costs. 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. Sharma *et al.* (2014) explain that insights alone does not lead to decision, and that a key component is decision acceptance by subordinates which influences their motivation and thus leads to better implementation.

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 (Lönqvist & Pirttimäki 2006). Davenport and Harris (2017) provide several success stories from data-driven organisations such as UPS, Amazon, Netflix, Google, and Continental airlines all of which were able to achieve better performance by reducing costs, increased sales, increased customer satisfaction, optimizing risks, and leveraging on new opportunities. Raguseo and Vitari (2018) using a survey of 76 responses supported similar findings, showing that big data analytics contributed directly and indirectly to financial performance through increased customer satisfaction.

5. METHODOLOGY

This article follows the quantitative methodology since the primary aim is to test several hypotheses from existing theories and examine relationships between the dependant and independent variables.

This study was conducted in metal rolling plant in KwaZulu-Natal with approximately 2,000 employees which dealing in both local and international exports of rolled coils to consumer conversation plants which create end products such as vehicles, beverage cans, foils, cookware and so forth. The company has several sites across South Africa. However, this study was conducted at the headquarters where most information works are located. The company embarked on implementing a business analytics implementation in 2014. 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. Only workers with a valid SQL server reporting services client access licence were considered in this study. A BI usage report indicates that only 67 users reflected enough report runs. This represented the population for the study. The response rate was 64.1%, which represents 47 responses out of a total of 67. The responses consisted of half managers and the other half non-mangers. The

respondents with more than ten-year experience in BI represented 21% of the population versus 25% of respondents with less than two years' experience in BI. More than half of these employees use BI daily.

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 were chosen which 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 was deployed using the five-points Likert scale from strongly disagree, disagree, neither agree nor disagree, agree and strongly agree. The survey was distributed via an email link, with the informed consent attached whereby participants could fill in the responses. Once enough responses were 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 the findings follow.

6. FINDINGS AND DISCUSSION

6.1. Cronbach Coefficient Alpha

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

Table 1: Cronbach's Alpha's Table for Internal Consistency. Source: SPSS Output Survey Results

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

6.2. Correlation

6.3. 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 so

Table 2: Pearson Correlation Results. Source: SPSS Output Survey 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 0.05 level (2-tailed).
 **Correlation is significant at the 0.01 level (2-tailed).

as 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.

$$Decision\ Quality = \beta_1(Information\ Quality) + \beta_2(System\ Quality) + \beta_3(Service\ Quality) + Error + Constant$$

The assumptions of linear multiple regression are: (i) linearity and additivity, (ii) independence of errors or lack of autocorrelation, (iii) homoscedasticity, (iv) multivariate normality and (v) No multicollinearity (Leech, Barrett & Morgan 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 Durbin-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.

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 which complies.

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

Correlation denoted by R measures the strength of the relationship. It does not guarantee the cause and effect relationship, but it 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.

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

6.4. Hypothesis Testing

The null hypothesis was:

Table 3: Multicollinearity Test. Source: SPSS Output Survey Results

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

^aDependent Variable: Decision Quality.

Table 4: Multiple Regression Summary. Source: SPSS Output Survey Results

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

^aPredictors: (Constant), BI Team Service Quality, Information Quality, System Quality.

^bDependent Variable: Decision Quality.

Table 5: ANOVA. Source: SPSS Output Survey Results

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			

^aDependent Variable: Decision Quality.

^bPredictors: (Constant), BI Team Service Quality, Information Quality, System Quality.

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

The three-research hypothesis are

H₁: Information Quality has a positive impact on the quality of decision-making using BI

H₂: System Quality has a positive impact on the quality of decision-making using BI

H₃: BI Service Quality has a positive impact on the quality of decision-making using BI

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

H₁: information quality was found to have a strong positive significant relationship to decision quality with a correlation value of .547** at the 99% interval.

H₂: 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.

H₃: 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 H₁, H₂, H₃ 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.

7. CONCLUSION AND RECOMMENDATIONS

The paper gives a snapshot of the factors influencing decision-making using business intelligence at a metal-rolling company in KZN. All the objectives were achieved in the study. 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.

The recommendations are:

- 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 create initiatives such total quality management together with statistical process control in order to ensure a high quality of accurate data.
- Become more ambidextrous by pursuing both strategic and operational BI objectives and building both capabilities simultaneously. Operational capabilities yield quicker gains and operational efficiencies whilst strategic capabilities will make the company more competitive. The company must focus on using information and insights from daily operations to streamline activities. It must also focus on using information about new opportunities or threats and orientate towards risk-taking and discovery yield new innovative products and services.
- Seek opportunities of Big data analytics and IoT with cloud computing which offers reduced capex costs on infrastructure and outsourced

capabilities, it can lead to many benefits with improved customer satisfaction and improved financial performance as well as financial inclusion policies (Thulani, Chitakunye & Chummun 2014).

- Utilize more sophisticated BI 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). Implement real-time warning alerts which have shown to improve decision making (Delen *et al.* 2018).
- 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. Craft plans and a structure to attract, retain and improve people with technical and analytical skills.

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