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The Use of Data Analytics in Strategic Decision-Making in a South African Pay-TV Company

BUSA7417A Research Project

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WITS Business School

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Thesis presented in partial fulfilment for the degree of Master of Business Administration to the Faculty of Commerce, Law, and Management, University of the Witwatersrand

April 2021

Declaration

I, Prebashni Reddy, declare that this research report entitled 'The use of data analytics in strategic decision-making in a South African Pay-TV company' is my own, unaided work. I have acknowledged, attributed, and referenced all ideas sourced elsewhere. I am hereby submitting it in partial fulfilment of the requirements of the degree of Master of Business Administration at the University of the Witwatersrand, Johannesburg. I have not submitted this report before for any other degree or examination to any other institution.



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Signed at Johannesburg on 30th April 2021

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Abstract

The extent to which data and analytics inform decision-making in the Pay-TV industry in South Africa is not known. Netflix used data to achieve a competitive advantage and became a leading player in the streaming services arena. Blockbusters no longer exist because they did not change with the times and listen to what their customers wanted. Companies must use the data that they collect to make decisions and remain relevant in a continually evolving business environment. This research aims to evaluate the extent to which senior management use data and analytics to make decisions. The study measured the relationship of each of the following 3 constructs: data literacy, data accessibility, and data usage with data-driven decision making. The researcher carried out an exploratory study employing a quantitative and observational design approach. Adopting a cross-sectional methodology and drawing on a purposive nonprobability sample of senior managers from a South African Pay-TV company. An online structured interview survey was used to collect data from a population of 294 senior managers who were assumed to be decision-makers. The findings of the study were that data usage, data literacy, and data accessibility each have a positive relationship with data-driven decision-making. The research identified opportunities for the South African Pay-TV company to improve the use of data in decision-making for better- informed decisions and better business performance through a 3-step programme which was recommended should form part of their data strategy. To improve data literacy amongst senior management and other decision-makers a continuous programme of training in the skills to interpret and understand data and analytics is recommended as the first step and arguably most important step. Crafting and implementing an accessibility strategy is the next step and driving usage of that data and analytics is the last and crucial step in the programme. The findings of this study supported by previous research indicate that this company will improve performance and outperform its competitors with the use of data in decision making.

KEYWORDS: Evaluating, Data, Analytics, Decision-Making, South Africa, Pay-TV Company, Data Literacy, Data Accessibility, Data Usage

Dedication

This study is dedicated to my parents. They both come from backgrounds that did not allow them to study further or even complete high school for that matter. They rose above that to become successful. They provided my sister and me with a great life, including education and a love of learning. Thank you for your hard work and sacrifice that enable me to be who I am and made it possible for me to achieve everything that I have so far.

To dad, thank you for instilling in me the love for learning and the importance of education.

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1. Introduction to the Research Report

According to MacAfee, Brynjolfsson, and Davenport (2012), "We are living in the Age of Data". New data is being produced from all industries at a phenomenal rate. The growth in new sources and the actual data available is growing exponentially. Constantiou and Kallinikos (2015) state that many organisations, worldwide, have invested substantially in data and the analysis thereof to create value from the data that is collected. This research study aims to evaluate the use of the data collected and processed, and the analytics performed on that data in the decision-making process at a South African Pay-TV company.

In this chapter, the researcher introduces the report by providing the context and background of the study. Here, the researcher described the company observed as well as why it was chosen. The researcher then conceptualises the research by means of the research problem statement and the research purpose statement. Research questions and the accompanying research hypothesis are put forward. The delimitations and assumptions of the study are discussed and, finally, the significance of the study is articulated.

1.1 Context of, and Background to, the Study

The Pay-TV company being studied positions itself as Africa's leading entertainment company. It creates local content and secures the rights to international content. This content is delivered into the homes of its subscribers via Direct-to-Home (DTH), Digital Terrestrial Television (DTT) and online video entertainment services. Its entertainment platforms serve over 14 million subscribers in 50 countries in Africa. The company has two main revenue streams; selling advertising to its media partners, and subscription revenue that gives subscribers access to the content available on their platforms, Multichoice (https://www.multichoice.com).

The data collected on subscriber's viewership habits help to inform decisions on what content to purchase and which rights to terminate, where to place advertisements, and how to promote their content to their subscriber base via recommendation engines. The amount of data collected, stored, processed, and analysed is enormous. It is collected at a transactional level per second for most, if not all, the platforms and systems. This enables the company to

operate successfully. The magnitude of data available creates numerous opportunities to add value to the business.

The researcher considered the question: to what extent is the data and analytics being used to drive data-driven decisions, if at all? The research laid out in this report seeks to answer the question.

Mikalef, Framnes, Danielsen, Krogstie, and Olsen (2017) define big data analytics capability as the ability of the organisation to capture and analyse data with the intent of generating insights. This is achieved by deploying data, technology, and staff. Gupta and George (2016) concur and state that resources are leveraged towards a business objective. The approach and definition referred to above will be used in this study. The study will not be limited to big data analytics but will encompass all analytics.

To create a capability that is difficult to imitate and transfer, Vidgen, Shaw, and Grant (2017) recommend that organisations attain and develop a combination of data, technological, human, and organisational resources. Chen, Chiang, and Storey (2012) found that big data analytics is about analysing large volumes of data from many different sources, generating actionable insights that can help organisations gain a competitive edge. Wamba, Gunasekaran, Akter, Ren, Dubey, and Childe (2017) supports this by adding that insights generated from data are relevant in organisations where making informed decisions is critical.

Although the value of data in decision-making is growing in importance as Abbasi, Sarker, and Chiang, (2016) have noted, increasingly organisations are investing heavily in technologies that produce analyses of data, which encourage data-driven decision-making. Recent studies by Popovič, Hackney, Tassabehji, and Castelli (2018) and Wamba et al. (2017) have found that many organisations fail to capture value from their big data investments.

It is for this reason that this study was conducted, to evaluate the extent to which the South African Pay-TV company is realising value from its investments in data by utilising the insights generated from the analyses thereof.

1.2 Research Conceptualisation

1.2.1 The Research Problem Statement

With the rapidly changing business environment and technology moving at the pace that it is, businesses can collect more data and more types of data, than they previously ever could. Executives and other decision-makers have a lot more information at their fingertips to base their decisions on (Ranjan, 2005).

The pace of technology is changing Business Intelligence as a whole. Not only is more data available, but the speed at which data can be turned into information from which actionable decisions can be made, is also increasing (Duan and Xiong, 2015). Deloitte Analytics and KPMG have claimed that data is the new gold and that the challenge is to mine it.

New terminology and buzzwords that did not exist a few years ago, to describe data and its collection, storage and use have become commonplace. These terms include Big Data, Artificial Intelligence, Machine Learning, and Deep Learning. The emerging roles required to support these functions have given rise to professional designations such as Data Scientist, Data Engineer, and Chief Data Officer. These are increasingly becoming mainstream professions. Companies are using data analytics and data-driven decision-making to derive a competitive advantage (Davenport and Harris, 2007).

The extent to which data and analytics informs decision-making in the Pay-TV industry in South Africa is not known. This research aims to evaluate the extent to which senior management use data and analytics to make strategic decisions in one such company.

According to Kudyba (2014), Netflix uses data to achieve a competitive advantage to become a leading player in streaming services. Blockbusters had to cease operating because it did not consider what the data was telling them about customer requirements and preferences and did not change their service offering accordingly. The two examples mentioned above highlights the importance of using the data that companies collect to make informed decisions and remain relevant in a continually evolving business environment.

The research purposes to answer the question 'to what extent does the data collected, stored and analysed supports, if at all, decision-making at a South African Pay-TV company?

1.2.2 The Research Purpose Statement

The research aims to understand to what extent the investment in data collection, storage and analysis is being realised by its use in decision-making by senior managers.

The objective is to evaluate if data and analytics are supporting decision-making in the Pay-TV company. This will be achieved by establishing the extent to which the data and analytics are being used by senior management. The research will consider the degree to which senior management, who are to use the data and analytics, are data literate. The extent to which they have access to the information that they need to make these decisions will also be considered.

Since the aim of this research study is to add to the body of knowledge in this field, it is essential to have a comprehensive understanding of the existing body of knowledge. Therefore, a critical first step in the research process is to review the published literature. The literature review for this research was focussed on uncovering and understanding the generally accepted facts of the subject at hand and to establish the current philosophies which have been used by previous researchers in the field.

In the first section, existing literature on the subject is reviewed to understand, critique, and finally explain how data is used in decision-making in the South African Pay-TV context. Recommendations are proposed based on the findings of the study.

In the second, the research approach that is being used is described by detailing the research paradigm, research strategy, research design, research procedure and methods that were deemed appropriate to discover and analyse how senior management at the South African Pay-TV company currently make decisions.

In the third, data was collected and analysed. The aim was to determine if the data and the outputs produced by analysing the data are, in fact, supporting senior management in making the decisions necessary to meet the strategic objectives of the company.

The final section considers if, based on the analysis of the data collected, the findings demonstrate that data is being used as a strategic tool. It makes recommendations about the best use of analytics to create a data-driven culture in the organisation.

1.2.3 The Research Questions and Accompanying Research Hypotheses or Research Propositions

1.2.3.1 Is there a relationship between the use of data and analytics by senior management and data-driven decision-making?

H_0 - The use of data and analytics by senior management has no effect on data-driven decision-making

H_1 - The use of data and analytics by senior management positively influence data-driven decision-making

1.2.3.2 Is there a relationship between data accessibility by senior management and data-driven decision-making?

H_0 - There is no relationship between data accessibility and data-driven decision-making

H_1 - There is a positive relationship between data accessibility and data-driven decision-making

1.2.3.3 Is there a relationship between the data literacy of senior management and data-driven decision-making?

H_0: There is no relationship between the data literacy of senior management and data-driven decision-making

H_1: There is a positive relationship between the data literacy of senior management and data-driven decision-making

1.3 Delimitations and Assumptions of the Research Study

According to Theofanidis and Fountouki (2018), delimitations are limits that are set by the author of a research study that he/she intentionally states and positions for the body of research. By doing so, the author is focussing the research more narrowly, as these are author-defined boundaries and confines that make the study more manageable and achievable.

This research will focus on senior management currently employed at a South African Pay-TV company. This focus was chosen because senior managers are expected to make decisions regularly to meet the strategic objectives of the company. The results may not necessarily reflect how all senior management use data to make decisions in other companies or in the industry or country. The company operates in 50 African countries, including South Africa. Some of the senior management team members are based in Dubai, United Arab Emirates. This study includes all senior management from Africa and Dubai. The scope is therefore limited to, and is concentrated on, employees that are currently employed at the company, regardless of which region they are based in.

The COVID-19 pandemic also impacted the study. Although the pandemic resulted in limitations that were not chosen by the researcher, they are worth noting as it limited the ability and capacity of respondents to respond to the survey. The company under discussion Working from home has created additional challenges and longer working hours for employees, resulting in many respondents being too busy to fill in online surveys. Without face-to-face interviews and personal interactions to motivate for participation the response rate to the survey suffered.

The critical assumption in this research paper is that a large proportion of senior managers use the results of analyses in the form of deep-dive analytics and visualisations like dashboards and reports to make strategic decisions. The findings of this paper will either substantiate that assumption or refute it. Another key assumption is that decision-making forms a large component of the senior management role. To further verify this, senior managers were asked whether they made decisions in their current role. The answer to this determined if they were included in the analysis and discussion of the findings of the study.

1.4 Significance of the Research Study

This research aims to contribute to the body of knowledge by generating information that the company can use to optimise decision-making and to derive the full value of its investment in data collection, processing and analytics. It also serves as an example of a Pay-TV company to other academics interested in pursuing this subject as an avenue of research.

As there were previously no South African or African-concentrated research available on the Pay-TV industry, the expectation is that this research will, at the very least, provide some insight into this topic. The expectation is that the company, and the larger Pay-TV industry, will be able to use this as a guide and reference on how to best position themselves as an entity that is on the cutting edge of the data and analytics revolution..

2 Literature Review

2.1 Research Problem Analysis

According to Constantiou and Kallinikos (2015), managers are increasingly basing their decisions on insight generated from big data. Mikalef, Boura, Lekakos, and Krogstie (2019), Raghupathi and Raghupathi (2014), Waller and Fawcett (2013), and Wang, Ngai, and Papadopoulos (2016) have shown that substantial value has been derived from applying big data to problems in many industries including healthcare, service provision, supply chain management, and marketing. Additionally, Ransbotham and Kiron (2017) have found that organisations that are leaders in adopting big data are more likely to deliver new products and services, and it, therefore, creates a source of innovation. Story, O'Malley, and Hart (2011) concur that the effectiveness of marketing activities can be improved by using big data and possibly lead to incremental innovation. Sharma, Mithas, and Kankanhalli (2014) found evidence to support that business value can be created through big data analytics.

According to Lycett (2013), the widespread use of technology in this age has turned the average consumer into a non-stop producer of data, and the richness of this data is changing the way businesses make decisions. This allows managers who have access to rich, insightful, and current data to make better decisions based on evidence rather than intuition or laboratory-based consumer research.

2.2 Research Knowledge Gap Analysis

Mithas, Lee, Earley, and Murugesan (2013) offer the view that although there are numerous benefits from implementing a big data strategy and investing intensively in the technologies to support it, many organisations are failing to optimise on big data. Mayer-Schönberger and Cukier (2013) and Satell (2014) expressed the view that although big data is heralded as the new capital in the current super competitive environment, converting big data into a competitive advantage is a complex process. It is due to this, as Mithas et al. (2013) adds, that more than half of big data projects do not achieve their goals.

Yi, Liu, Liu, and Jin (2014) refer to data as digital oil because there is so much value in it. They agree, regardless of where the data is generated from or shared to, the real challenge is to analyse it in a way that creates value. Berners-Lee and Shadbolt (2011) call it the "New Raw Material of the 21st century". Chen and Zhang (2014) refer to it as rich business intelligence that enables better-informed business decisions.

The challenges, however, are significant as many researchers highlight. Like Gandomi and Haider (2015) who provide insight into data integration complexities. Kim, Trimi, and Chung (2014) put forward their opinions on the lack of skilled personal and sufficient resources, whilst Barnaghi, Sheth, and Henson (2013) offer critical discussions of data security and privacy issues. Several others elucidate challenges including inadequate infrastructure and insignificant data warehouse architecture, as pointed out by Barbierato, Gribaudo, and Iacono (2014) and synchronising extensive data by Jiang, Chen, Qiao, Weng, and Li (2015).

For the purposes of this study, we focus on the use of this data after all the challenges have been overcome. However, the analysis and insights themselves can present problems, including data literacy of the audience.

As Davenport and Dyche (2013) state, big data analytics is more than merely collecting, classifying, comprehending, and quoting data. Weill and Ross (2009) admit that although it is challenging, for a company to become data-driven, they encourage the alignment of people, technology, and organisational resources. The way data and insights are relayed and presented to the business audience is fundamental and is a crucial part of this study.

Exploring the level of interpretation and understanding of analytics and insights are essential factors in the use of these for decision-making. Taheri, Zomaya, Siegel, and Tari (2014) point out that visualising data concerns making the data easier to read and interpret through graphical representations and tables. This is one factor that helps the audience ingest the data quickly and easily.

Watson (2014) highlights descriptive analytics which illustrates what has happened already. The latter could be presented through reports, dashboards, scorecards, and data visualisations. Some business areas find a forward-looking view more valuable, and this is the gap that predictive analytics purport to fill. It aids in forecasting and can also be represented on dashboards or scorecards. A recent industry survey by PWC indicates that many companies do not exploit the benefits that big data offer. This is the gap that the researcher has identified and wants to explore. The underlying actions that lead to the use of analytics warrant closer investigation.

Senior managers need to make decisions as a core part of their roles. The presence of easily accessible, reliable information contributes to effective decision-making. Information availability refers to the presence of, and access to, needed information. Gifford and Bobbit (1979) say that the availability is high if the data are available at the time when it is needed and are easily accessible.

The research will seek to understand both the accessibility and understanding of the analytics available to assist decision-making. Davenport and Harris (2007) and Davenport (2006) describe many examples of the successful use of data and analytics and offer several managerial strategies for successfully exploiting their potential.

To generate value, insights, which refer to a deep and intuitive understanding of phenomena, need to be leveraged by managers into strategic and operational decisions (Sharma, Reynolds, Scheepers, Seddon, and Shanks, 2010; Lycett, 2013). When an organisation's capacity to produce increasingly sophisticated analytics outpaces managers' abilities to understand, discomfort is created. Managers find they must make decisions based on complex analytical insights that they may not yet fully understand. Yet, despite this discomfort, these managerial decisions must be made. Davenport (2006) states that securing the right resources and leadership means companies should concentrate on tools, technology, and talent management.

2.3 Framework for Interpreting Research Findings

In this section, we will identify and review frameworks that could be employed to interpret our research results. The components of the research, like attributes and variables, will be compared to the theories and frameworks that are part of the field of study that this research belongs to. Adom, Hussein, and Agyem (2018) posit that a theoretical framework is a one that has its foundation in a stable theory in the field of examination which is related to the hypothesis of a study.

The framework that the researcher adopted for this research study, and by which the research results will be interpreted, is the Adaptive Structuration Theory. The Adaptive Structuration Theory was established by DeSanctis and Poole (1994). According to Rice (1984), the theory is based on the view that technology must improve the lives of employees and the organisation through improved efficiency, productivity and satisfaction. DeSanctis and Poole (1994) proposed it as an approach to study the role that information technology plays in carrying out organisational change. It considers the change process from two points of view; the structures that are offered by technological advances, and the structures emerging from human actions when interacting with this technology.

Campbell (2015) explains how adopting this theory helps the evolution of teams as well as organisations by facilitating the interactions of employees through information technology. It is for this reason that this theory was selected as it adequately addresses how better decision-making by senior managers create a more effective and engaged employee corps.

Since structures, processes, and systems coexist and have a causal relationship, it would be meaningful to explore the notion of data-driven decision-making and its implications at this South African Pay-TV company.

2.4 Summary and Conclusion

It is imperative for managers and decision-makers to use the colossal amounts of data at their disposal to make informed decisions, rather than relying on intuition or experience. Research has shown that, globally, numerous companies have used data and analytics to achieve a

competitive advantage over their competitors. It is also clear that many organisations do not realise the value of their data efforts.

The reasons for not fully utilising the insights derived from the data could be challenges such as data literacy levels in organisations, access to the right data at the right time, too much data to sift through, the lack of skills needed to interpret what is being relayed. A disconnect between the person drawing the insights and the person interpreting it may exist. The decision-maker may also not be able to act on the insights. Whilst the material considered for the literature review offers some insights and guidelines to address these issues, the aim of this research study is to understand whether the same holds true for the South African Pay-TV company where the research was undertaken.

3 Research Strategy, Design, Procedure and Methods

Chapter 1 conceptualised the questions that this paper attempted to answer: 'To what extent are senior managers at a South African Pay-TV company using data to drive their decision-making?', 'What is the relationship between data literacy and data-driven decision-making?' as well as 'What is the relationship between data accessibility and data-driven decision-making?'

In Chapter 2, a review of available and relevant literature was done to establish a foundation to construct the study. It provided an understanding of what research has been done and where the gaps are. While a few industries have been focussed on in the research reviewed, such as Supply Chain Management, Retail, eCommerce, and Medical, there was minimal research about the Pay-TV industry, which led to this study. The literature review also clarified the research approach.

In this chapter, the methodology adopted to collect and arrive at the findings as well as the conclusions will be elucidated. It will outline the methodology selected to answer the questions put forward by this research paper. In addition, this section will describe the research paradigm, research design, research instrument, the population targeted, the sample selection, and the data collection process. It details the consistency and soundness of the research approach and the limitations of the study, which in turn lends itself to the credibility of the report.

Nyce (2007) found that studies can be causal, descriptive, or predictive. He defines predictive studies as predicting a future consumer decision or event using current or historical information. A predictive approach is not relevant to this research as it is not attempting to predict decision-makers' behaviour.

Brains, Willnat, Manheim, and Rich (2011) state that causal studies investigate cause-and-effect relationships. The approach was also rejected, as this study was not attempting to measure or change decision-makers' behaviour through manipulation.

The researcher decided on using a descriptive and statistical study approach as the research was aimed at investigating and describing how senior managers make decisions at a South African Pay-TV company. The way decisions are made is descriptive or characteristic of senior management. The research was a once-off study using statistical analysis to extrapolate population characteristics from a statistical sample. The research was conducted in field conditions; and focused on senior managers who make business decisions.

3.1 Research Paradigm

According to Smith (2017), three main research philosophies exist, positivist, interpretive, and critical approaches. Bryman (1992) outlines the positivist approach as a scientific method of inquiry, which includes testing or verifying theories or explanations. Creswell (2014) has associated each research methodology with a particular worldview. He links post-positivists with quantitative research. Both Ismail and Zainuddin (2013) and Smith (2017) suggest that the interpretive and critical approaches apply a qualitative and subjective understanding of a research topic by focusing on insights and judgements of subjects.

At the same time, Creswell (2014) associates constructivists and transformative worldviews to qualitative research. Constructivists posit that individuals want to find meaning in the world and develop subjective meaning, whereas transformative worldview incorporates politics, political change, and social oppression.

The research paradigm for this study was selected by bearing in mind the aim of the research and the advantages and disadvantages of each of the three philosophies suggested by Smith (2017). This study relied on statistical tests to derive results, so the positivist approach was identified as the best fit to achieve the research aims.

Of the benefits put forward by Ismail and Zainuddin (2013), the two that were relevant to this study were: the application of statistical tests allow for reliable empirical evidence to be derived, and the results of the research are not subject to bias because the research remains independent.

Cavana, Delahaye, and Sekaran (2001) highlight the disadvantages of the positivist research approach. They state that it assumes that respondents share common thoughts and feelings, the use of statistical tests masks the researcher's subjectivity and involvement, and samples are homogenous so generalisations cannot be applied to specific groups.

3.2 Research Strategy

While Opie and Brown (2019) distil research strategies into two types, namely quantitative, using numerical analyses, and qualitative, using words and meanings, Smith (2017) finds that both are acceptable provided that the most appropriate method is selected. Creswell (2014) states that quantitative research focuses on testing objective theories by evaluating the relationship between variables.

He adds that quantitative research is characterised by using numbers and closed-ended questions. The assumption is that theories are tested deductively, and findings can be generalised and replicated. Bryman (1992) indicates that quantitative research can be conducted in several ways, including using surveys and experiments and analysing previously collected data.

Some of the limitations of quantitative research include results that are limited as they provide numerical results rather than detailed description and human perception. According to Smith (2017), unlike the qualitative approach, the quantitative approach does not have the drawbacks of data completeness gaps or concerns around the data analysis process being subject to bias by the researcher.

As Creswell (2017) elaborates, qualitative research uses sentences, narratives and words which is not appropriate for the statistical analysis, which this research study required. Bryman (2015) states that quantitative research 'emphasises quantification in the collection and analysis of data'. Furthermore, Bell, Bryman, and Harley (2018) add that due to the scientific nature of the quantitative research methodology, they are usually robust and unambiguous because of the exactness of the measurement standards.

Rahi (2017) posits that this employs a fresh collection of data from a significant population which aligns to the research problem or question and results in extensive analyses being performed on the data. Brannen (2016) supports the quantitative approach and recommends it when there is a specific research problem that requires direct responses from participants.

The researcher adopted a quantitative methodology because it was best aligned with the research problem outlined earlier. The quantitative approach was the best match for this research because the questions were closed-ended and required precise answers. The topic itself was scientific in nature, so the questions and analysis of responses lent itself to a quantitative approach. Additionally, the population was large, which would have made the interpretation of qualitative responses very challenging. The nature of quantitative questionnaires facilitates anonymous responses.

It was considered the most appropriate approach because it allowed for an objective measure and quantification of data and analytics in decision-making at the South African Pay-TV company under observation (Leedy and Ormrod, 2015).

3.3 Research Design

Bryman (2015) described the research design as a framework for the collection and subsequent analysis of data. Creswell (2013) suggested that designing the research is necessary to determine how to collect data and the instrument to be used. Zikmund, Babin, Carr, and Griffin (2013) described the research design as the roadmap of how to go about collecting and analysing the required data.

According to McNabb (2015), a good research design aims to ensure that enough correct or relevant data is collected to address the research problem wholly and precisely. Zikmund (2013) agreed, stating that it is imperative for the data collected to be related to the research problem.

Bryman (2015) recommends conducting a quantitative cross-sectional (occurring at a particular point in time) survey using a self-completion questionnaire which is meant to collect

data relating to two or more variables. Zikmund et al. (2013) concur that survey design aids in sampling and data collection at a specific point in time.

The cross-sectional design was deemed the ideal one for this study because it best suited the type of data that needs to be collected and was relatively quick, easy, and inexpensive to set up. This design study was observational in nature and enabled the analysis of data from a population, or a sample of a population, at a particular point in time.

The data could be grouped and analysed to discover patterns in the data, Bryman (2012). This made perfect sense for this study because the senior management at the South African Pay-TV company under observation were surveyed based on their experiences at a specified point in time. They have demanding jobs and do not have time to participate in lengthy and time-consuming interviews.

The user experience was convenient and quick to maximise the number of questionnaires completed. Data and analytics are rapidly changing, so the study must be limited to a point in time. The conditions at the time that the research was undertaken was also taken into consideration when choosing this approach. It was conducted during the coronavirus pandemic when globally, many companies, including the one in this study, followed the remote working and work from home approach.

3.4 Research Procedure and Methods

3.4.1 Research Instrument

A data collection instrument is a mechanism used to collect data. The observation schedule, questionnaires and the interview schedule are common types of data collection instruments. Data collection instruments have three common structures: unstructured, semi-structured and structured, (Kalof, Dan, and Dietz, 2008). The researchers found that surveys are an excellent way to test a hypothesis and to measure variables, such as attitudes, behaviours, and traits in a population. The surveys are useful in determining any potential links or relationships between variables. Survey research using questionnaires is a valuable tool for collecting data from a population.

The advantages are consistency, reach and simplicity. Creswell (2014) found that questionnaires display trends, attitudes, and opinions of a population by studying a sample of that population. Questionnaires are easy to create and distribute, making it simple to collect and analyse data.

Neuman (2013) points out that the instrument should be cross-sectional; this means that it gathers data at a point in time. Kalof, Dan, and Dietz (2008) concur that questionnaires are an easy way to collect data in a limited time. The questionnaire has close-ended questions meaning that respondents answer from predetermined choices, making it a lot easier to quantify and analyse.

Close-ended questions are usually a lot easier for respondents to answer as respondents do not need to seek assistance in answering them. Bryman (2012) agrees that this type of questionnaire has most of the benefits of a structured interview. Neuman (2013) states that instrument content development is an essential step in conducting a research study. This is where the question and hypothesis proposed are articulated into specific questions a research population could answer.

Kalof, Dan, and Dietz (2008) caution against poorly structured questionnaires which could lead to the collection of inaccurate information. Another potential pitfall is a low response rate from respondents which can affect the accuracy of findings. McNabb (2015) advises that questions should be concise and straightforward. Bryman (2012) advises that short questionnaires with clear instructions and layouts have better response rates.

The appropriate structure for this study was a structured approach. An online questionnaire with closed-ended questions that the respondent could complete by themselves was the best fit for the busy individuals who formed part of the population. This was in line with the suggestion by Bryman (2012) that stated that structured interviews that are self-administered are quicker to administer. Bell et al. (2018) agreed that it is cheaper and eliminates the unconscious biases that creep into face-to-face interviews.

In addition, the coronavirus pandemic has prescribed remote work and social distancing, thus making an online survey the most convenient and appropriate data collection method. Qualtrics was selected as the platform for this study because it was cost-effective and easily managed. The functionality of viewing how many responses were received and the ability to resend or remind the target audience that they have not responded made the management of responses and administration around this less cumbersome.

The online questionnaire consists of 21 close-ended questions (See Appendix A) which were formulated during the literature review. It measures four variables: data usage, decision-making, data literacy and data accessibility. Bryman (2015) describes a Likert scale as a multiple-item measure of feelings about a particular variable where a respondent is asked about their degree of agreement to a particular statement. The questions are on a seven-point Likert-type scale, ranging from 1-7 namely, Strongly disagree, Disagree, Somewhat disagree, Neither agree or disagree, Somewhat agree, Agree, and Strongly agree.

This structured survey questionnaire research instrument is designed as follows:

- Introduction to the researcher, the study, the aims of the study, and the reason for the study
- Contact details for both the researcher and supervisor are provided
- The respondent is advised that their responses are confidential which draws attention to the researcher's ethical consideration of a respondent
- The respondent is informed that they can stop at any time
- A qualifying question of whether they are a decision-maker is asked
- The 21 questions relevant to the study follow
- The respondent is thanked for their time and responses

3.4.2 Research Target Population and Sampling Methods

3.4.2.1 Population

According to Bhattacherjee (2012) and Sekaran, and Bougie (2013), a population is a group of people with the same characteristics that the researcher would like to study. Kalof et al. (2008),

explains a population as a collection of people that share a standard feature or interest. At the same time, Bryman (2012) defines the target population as a universe from where a sample is selected. Furthermore, Wotela (2017) describes a target population as an explicit group with information that a researcher wants. The population for this research study was the senior management of the South African Pay-TV company.

3.4.2.2 Sample and Sampling Method

Bryman (2012) defines a sample as a subset of the population selected to participate in a study. A crucial aspect of the research process is selecting a sample that it is both representative and unbiased (Remenyi and Williams, 1993). Smith (2017) warns that while sampling the entire population might enhance the representativeness and usefulness of the research findings; it is too expensive and cumbersome to attempt on a large population.

Wotela (2017) highlights that the sample of respondent's responses is extrapolated to the total population. According to Wotela (2017), probability and non-probability sampling are two types of quantitative sampling. He breaks these types down further into simple, systematic, convenience, and purposive sampling.

Zikmund et al. (2013) explain the concept of the purposive non-probability sampling method, as a well-informed individual choosing the sample based on his/her judgement concerning some attributes that the sample must have. Etikan, Musa, and Alkassim (2016) highlight that purposive sampling is subjective and criticised for not being a good representation of the population.

It was selected for this study because accurate randomisation is not possible. Tongco (2007), adds that the purposive sampling technique is the most effective method to apply when there is a need to study a domain with experts. This sampling methodology was used in this study because the population consisted of all senior management decision-makers at the company of interest.

The sample was a subset of this population. The population size was 294 senior managers, and the sample size was 122. The size of this sample was significant and enabled insights and extrapolation to the target population. The questionnaire was sent to the population to maximise the response rate for the generalisation of the study.

3.4.3 Ethical Considerations and Unintended Consequences of the Research

Ethical standards govern the way in which researchers conduct their research. Marzooqi (2015) states that the protection of participants and their informed consent is crucial. This was supported by Bryman (2012) who classified four items to consider in research ethics: informed consent, participant safety, deception, and invasion of privacy.

The Wits Business School has a policy that mandates that the researcher must obtain ethical clearance before any research begins. Appendix B. contains the application for ethical clearance from the relevant authority. Appendix G contains the ethical clearance certificate that was granted to permit the research study. The researcher committed to abide by all ethical expectations stipulated in the policy in the undertaking of this research study.

Consent had to be obtained from the company at which this research was conducted. This was requested in the form of a letter of permission to the Chief Data Officer of the South African Pay-TV company where the research was carried out. He granted permission and the documentation is attached as Appendix D.

Consent was sought from the individual participants before they started the survey through providing a yes/no option relating to their consent at the beginning of the questionnaire. Thus, selecting yes was explicit consent from the responder and completing the questionnaire was a sign of consent on the part of the participants.

The researcher ensured the participant's safety while participating in this study by keeping all responses anonymous. Furthermore, as part of the ethical standards enforced by the school, a plagiarism declaration was signed and attached as Appendix C as well as Appendix D, which contains the Turnitin report.

For the questionnaires and data collection component of the study, respondents were advised of the aims of the study and how their responses would be used, that their participation is voluntary, and no incentives were offered for participation. Respondents were assured that their responses would be kept confidential, the data collected will be stored in a secure place, and no respondents will be uniquely identifiable in the results. The above was stated at the beginning of the questionnaire before the question section.

3.4.4 Research Data and Data Collection Process

According to Wotela (2017), there are two broad sources for data collection; primary, which is the observation of participants, focus group discussions or interviews, and secondary, which refers to documents like census reports and government publications. Bryan (2012) states that the collation of data collected from the sample forms part of the data collection process to answer the research problem. Zikmund et al. (2013) advise that although secondary data is available, it rarely meets the needs of a research study. They recommend using primary data that is collected for the specific purpose of answering research questions.

For the purposes of this study, a primary data collection approach in the form of an online questionnaire administered by Qualtrics was used. The data collected will be stored securely on password-protected devices.

3.4.5 Research Data and Information Processing and Analysis

Neuman (2013) suggests that data analysis requires computer software to create statistical measures. The process defined in this research includes sampling the population, coding the datasets and finding the trends visible in the data. Polit and Beck (2008) recommend reducing, organising, and giving meaning to the data collected by performing analyses on the data. This will be done to extract useful information and develop conclusions to address the research questions. It was done in SPSS.

The demographic details of participants were collected to ensure that the sample was representative of the population. Descriptive, analytical statistics and regression techniques

were used to analyse the data collected. The sample was defined using the following descriptive statistics: frequency, percentage, mean, range, standard deviation, and total scores as well as regression, factor analysis, and coefficients.

Visualisations, tables and graphs were used to display the results. The survey data variables, namely data literacy, data accessibility, data usage, and decision-making were analysed to find relationships and associations between them.

Data was downloaded from Qualtrics and uploaded to SPSS for statistical analysis. It was verified, crosschecked, and updated for completeness and correctness.

3.5 Research Strengths—Reliability and Validity Measures Applied

Validity and reliability are terms used in quantitative research. For any research to be deemed sound it has to be tested for validity and reliability, Heale and Twycross (2015).

3.6 Validity and Reliability

According to Heale and Twycross (2015), the measurement of validity and reliability speaks to the quality of the research study that was undertaken. Validity and reliability are particularly important in quantitative research studies. Since a questionnaire was employed in this research the validity and reliabilty was measured.

3.6.1 Validity

Validity refers to whether the measure is true (Bolarinwa, 2016). Taherdoost (2016) adds that this specifically relates to the accuracy of a questionnaire or a survey research instrument.

3.6.1.1 External Validity

Cooper, Schindler, and Sun (2006) define external validity as the generalisability of the research findings to the population, while Weiner (2007) refers to it as ensuring that the findings from the sample will apply in real life and other contexts. The sample data collected was done across

different ages, genders, races, levels of work experience, and countries. This allowed the researcher to obtain valid results that could be generalised across the organisation.

3.6.1.2 Internal Validity

Cooper, Schindler, and Sun (2006) define internal validity as the accuracy of the research instrument used. They go on to add that it tests if the instrument measures what it says it is measuring consistently. Weiner (2007) states that it determines how well the research is done. As suggested by Field (2013), this study ensured internal validity by using the same questionnaire for the entire study. Additionally, the participants were randomly selected. The sample size was large. Both of these factors increase the likelihood of internal validity.

3.6.1.3 Construct Validity

Cronbach and Meehl (1955) state that construct validity is the extent to which the measurement is consistent with the theoretical constructs that are being measured. Weiner (2007) suggests three ways to test construct validity: convergent, divergent and factor evidence.

In this study exploratory factor analysis was conducted to determine convergent validity. According to Weiner (2007), this analysis tests if two measures of the construct are related. Factor loadings of greater than 0.4 were deemed valid and all 4 constructs were greater than 0.4. SPSS was used to perform exploratory factor analysis for all the item scales to determine the number of factors.

3.6.2 Reliability Testing

Nunnally (1978) refers to reliability as the instrument's ability to repeat the research findings and results. Weiner (2007) views it as consistent results upon repeated application. Cooper, Schindler, and Sun (2006) concur.

To ensure reliability, a standardised questionnaire was used and distributed to all respondents. Cronbach Alpha was used as a test for reliability. A high Cronbach's coefficient alpha indicates a higher reliability of the measurement scale (Cronbach, 1951). Nunnally and Bernstein (1994)

recommend an alpha above 0.7. Three of the four constructs in this research had Cronbach Alphas greater than 0.7. The decision to keep the fourth construct in the analysis was made because this is a management study, and the risk was deemed acceptable and non-threatening.

3.7 Research Weaknesses—Technical and Administrative Limitations

Although every effort to reach as many people in the population as possible was made, the inherent limitation of utilising purposive sampling is that the findings could be criticised as not being subjective or a good representation of the population (Bryman, 2015).

The findings of this study can therefore not be applied to other Pay-TV companies in South Africa or elsewhere, with reasonable confidence.

3.8 Summary

This chapter discussed the research methods used in the study. The research approach adopted is positivist quantitative. Online questionnaires with close-ended questions were used for data collection, which was analysed to provide findings and insights that answered the questions proposed by this study. The ethical considerations were laid out as well as the limitations of the study. The next chapter will reveal the results that were gathered from the online questionnaires. The results will be discussed against the findings of the literature review.

4 Presentation of Empirical Results

This chapter presents and interprets the data collected as part of the research study. The data was collected by using structured, online questionnaires completed by senior management, as defined by the Human Resources department, at the company. The purpose of the study is to evaluate the extent to which data is used in decision-making. The chapter begins with a presentation of the characteristics of the respondents, exploratory factor analysis to test validity and reliability of the measurement of scales, and regression analysis.

4.1 Data Screening

Table 4-1: Distribution of Demographic Questions that were Answered

	Gender	Age	Race	Education	Years in the company	Years in a decision-making role
Valid	122	122	121	122	122	122
Missing	0	0	1	0	0	0

Source: (Based on online questionnaires, 2021).

Of the total population of 294 senior managers, 124 responded to the request to fill in the questionnaire. Two questionnaires were incomplete and had to be deleted. The final sample size that was eligible for analysis was 122. Table 4-1 shows that 122 senior managers in the sample answered all six of the demographic questions except for one who didn't reveal their race.

4.2 Sample Characteristics

4.2.1 Gender Distribution

Table 4-2: Gender Distribution of Sample

	Frequency	Percent	Valid Percent	Cumulative Percent
Female	41	33.6	33.6	33.6
Male	81	66.4	66.4	100.0
Total	122	100.0	100.0	

Source: (Based on online questionnaires, 2021)

The gender distribution of the respondents shows that there were more males, 66%, than females. Twice as many males compared to females were sampled. Table 4-2 illustrates the how the sample is distributed by gender.

4.2.2 Age

Table 4-3: Age Distribution of Sample

	Frequency	Percent	Valid Percent	Cumulative Percent
30 - 39	40	32.8	32.8	32.8
40 - 49	57	46.7	46.7	79.5
50+	25	20.5	20.5	100.0
Total	122	100.0	100.0	

Source: (Based on online questionnaires, 2021)

Table 4-3 shows that most respondents (47%) fell into the 40 – 49 age group, followed by the 30 – 39 age group (33%) and the last 21% into the 50+ age group. This, together with the numbers of years of work experience, indicates that the sample is mature from a career perspective.

4.2.3 Race Distribution

Table 4-4: Race Distribution of Sample

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	African	29	23.8	24.0	24.0
	White	55	45.1	45.5	69.4
	Coloured	4	3.3	3.3	72.7
	Asian	29	23.8	24.0	96.7
	Other	4	3.3	3.3	100.0
	Total	121	99.2	100.0	
Missing	System	1	.8		

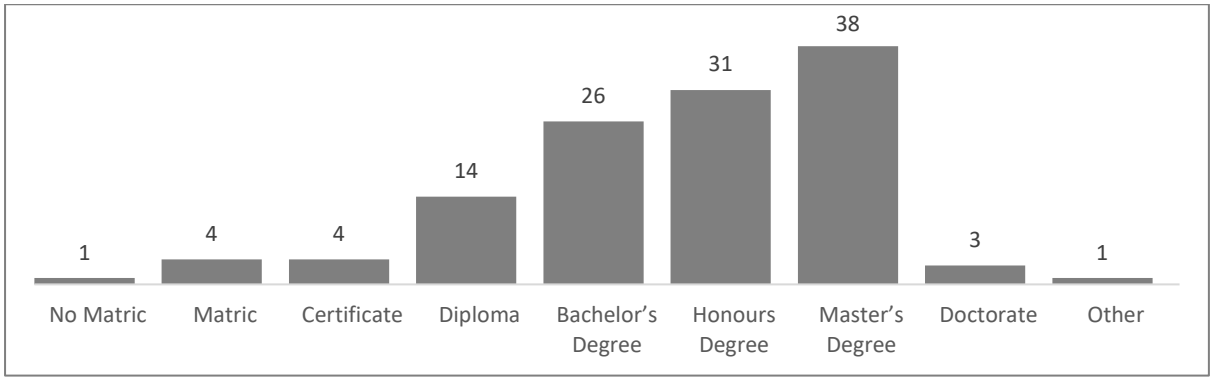
Total	122	100.0		

Source: (Based on online questionnaires, 2021)

The race distribution of the sample illustrates that most respondents were white (45%), followed by African and Asian, both at 24%, and Coloured and Other, both at 3% each. Table 4-4 displays how the sample is distributed by race.

4.2.4 Level of Education

Figure 4-1: Level of Education

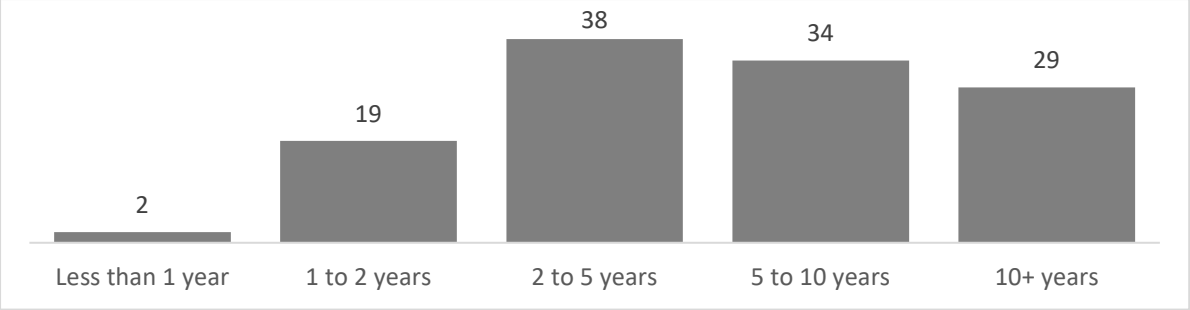


Source: (Based on online questionnaires, 2021)

This sample shows that respondents are highly educated with the largest number of respondents having a Master's degree (31%), followed by 25% with an Honour's degree, 21% Bachelor's degree, and 12% had a diploma. 3% each with a doctorate, matric, and certificate, and lastly 1% had no matric and 1% had answered other. Figure 4-1 displays the distribution by education in absolute numbers.

4.2.5 Number of Years in the Current Company

Figure 4-2: How many years have you been with your current company?

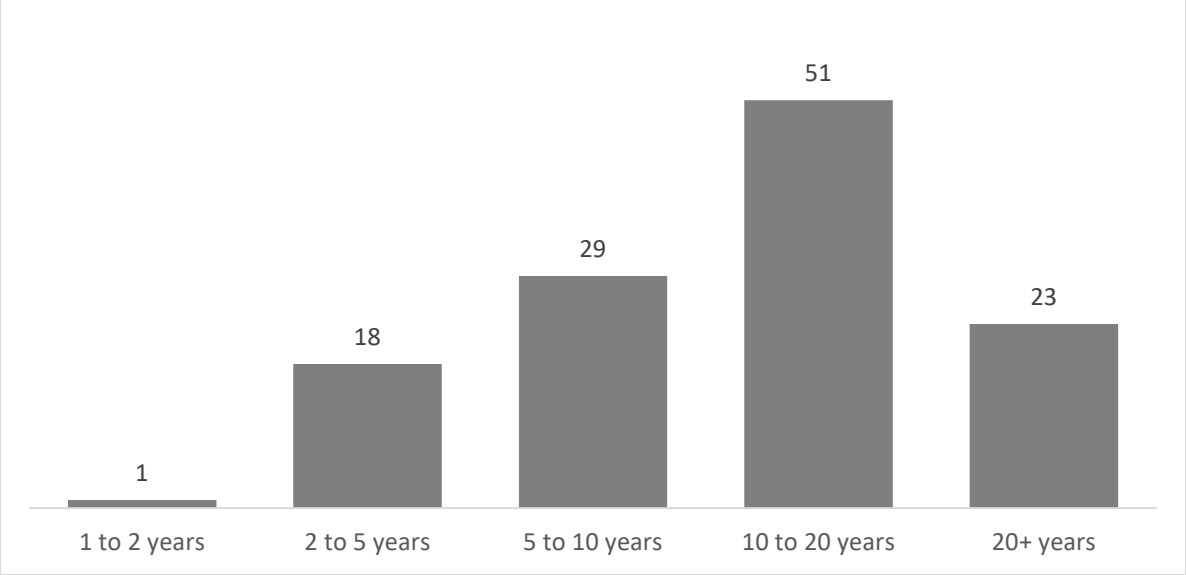


Source: (Based on online questionnaires, 2021)

More than half of the sample of senior managers have been with the company for 5 or more years (52%). The largest group was the 2-to-5-year group (31%), followed by 5-to-10-year group (28%), and 10+ years (24%), 16% were with the company for 1 to 2 years and 2% for less than one year. Figure 4-2 displays the distribution of number of years at the company in absolute numbers.

4.2.6 Number of Years in a Decision-Making Role

Figure 4-3: How many years have you been in a decision-making role?



Source: (Based on online questionnaires, 2021)

The distribution of number of years in a decision-making role show that the senior managers at the company have experience with most (42%) having 10 to 20 years of experience, followed

by 24% who have 5 to years' experience, 19% with 20+ years' experience, 15% with 2 to 5 years, and 1% with 1 to 2 years' experience. Figure 4-3 displays the distribution of total decision-making experience in absolute numbers.

4.3 Validity – Exploratory Factor Analysis

SPSS was used to perform exploratory factor analysis (EFA) for all the item scales to determine the number of factors. Additionally, it was used to examine the relationship between factors and their observed variables. The principal axis factoring (PAF) extraction method was used with Kaiser-Meyer-Olkin (KMO) and Scree plot. The Promax rotation method was used to optimise the factor structure. The recommendation by Field (2013) to use the pattern matrix instead of the structure matrix was adopted because of the ease of interpretation.

4.3.1 Sampling Adequacy

A check of the sample size to determine the adequacy of the sample was performed before the Exploratory Factor Analysis. Kaiser-Meyer-Olkin (KMO) is a measure of sampling adequacy. Hair, Black, Babin, and Anderson, (2010) state that a KMO greater than 0.5 is adequate and significant at $p<0.05$. Table 4-5 shows that the KMO for this study is 0.823 indicating that the sample size is adequate for factor analysis since it is greater than 0.5.

Table 4-5: Kaiser-Meyer-Olkin (KMO) and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.823
Bartlett's Test of Sphericity Approx. Chi-Square	1311.751
Df	153
Sig.	.000

Source: (Based on online questionnaires, 2021)

The Bartlett's test of sphericity was conducted to test that the original correlation matrix is an identity matrix and adequate for factor analysis (Hair et al., 2010). Table 4-5 shows the results of the Bartlett's test of Approx. Chi-Square =1311.571, DF=153, $p<0.05$ which indicate that the correlation between the items is sufficient and significant for factor analysis.

4.3.2 Extraction of Factors

The extraction method used is principal axis factoring and 68.38% of what is happening in the data was explained by 4 factors with 18 items when using the eigenvalue greater than 1 rule. Table 4-6 shows the results indicating this.

Table 4-6: Total Variance Explained

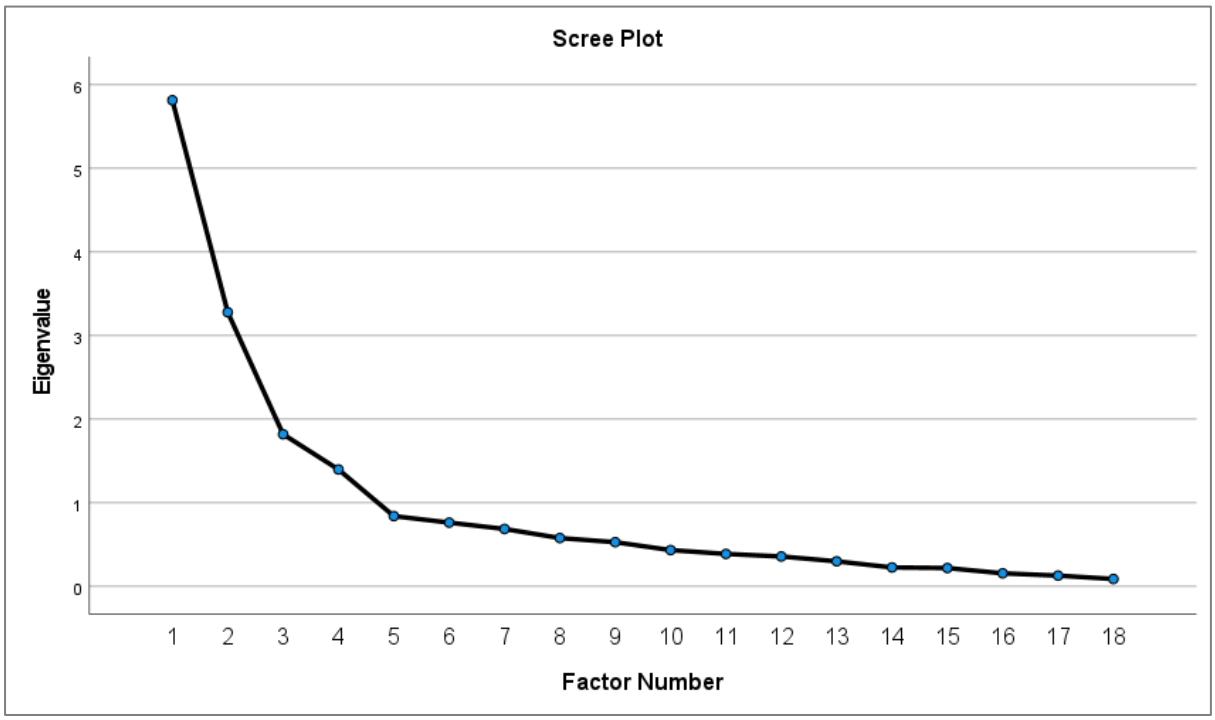
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	5.814	32.299	32.299	5.483	30.461	30.461	4.853
2	3.278	18.213	50.511	2.933	16.297	46.758	3.892
3	1.819	10.108	60.619	1.421	7.895	54.653	3.042
4	1.398	7.766	68.384	.817	4.541	59.194	1.201
5	.840	4.668	73.053				
6	.762	4.236	77.288				
7	.686	3.813	81.101				
8	.578	3.210	84.310				
9	.528	2.935	87.246				
10	.433	2.408	89.654				
11	.388	2.154	91.808				
12	.357	1.986	93.794				
13	.300	1.664	95.458				
14	.226	1.256	96.714				
15	.219	1.217	97.931				
16	.156	.866	98.797				
17	.128	.713	99.510				
18	.088	.490	100.000				

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

Source: (Based on online questionnaires, 2021

Figure 4-4: Scree Plot



Source: (Based on online questionnaires, 2021)

The Scree Plot in Figure 4-4 shows an inflection point at 4 and 5, which supports the answer in Table 4-6.

4.3.3 Rotation of Factors

Promax was chosen as the rotation method. The study started with 21 items resulting in 4 factors. After several iterations of trying to produce a clean matrix, only 18 items converged into 4 factors after rotation. Only factor loading of greater than 0.4 were included. Table 4-7 shows the 4 factors that were extracted. The decision-making factor has 6 items with factor loadings above the acceptable limit of 0.5 (from 0.517 to 0.924). Accessibility of data factor has 6 items from 0.558 to 0.889 while data skills had 3 items from 0.753 to 0.807. Data usage factor also had 3 items but one of which were below 0.5 and ranging from 0.494 to 0.544 (Field, 2013). Items that did not load or cross loaded were removed from further analysis. SK04 was removed because of no loading.

Table 4-7: Pattern Mix[a]

	Factor			
	Decision-making	**Data accessibility**	**Data skills**	**Data usage**
DM01	.924			
DM03	.913			
DM02	.879			
US02	.810			
SK03	.740			
SK02	.517			
AC04		.889		
AC06		.826		
AC03		.793		
AC02		.750		
AC05		.638		
AC01		.558		
SK05			.807	
SK07			.773	
SK06			.753	
US04				.544
US05				.527
US01				.494

Extraction Method: Principal Axis Factoring.

Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Source: (Based on online questionnaires, 2021)

4.4 Reliability Analysis

This analysis started with a total of 21 constructs or factors. After conducting the exploratory factor analysis and the Cronbach Alpha test only 18 factors were kept. The factors that were eliminated during the reliability analysis were dropped because they could not meet the set criteria for a reliable and consistent construct. The following factors were excluded; US03 was

removed from decision-making scale to improve scale, SK01 was also removed from Data skills scale to improve data, and SK04 was removed because of no loading.

Table 4-7 summarises the overall result from the scale reliability test of all the constructs, providing the number of items measuring each construct. Tables 4-8, 4-9, 4-10 and 4-11 show the Cronbach alpha per construct and the number of items. There were 18 constructs that were measured using Cronbach alpha, and the results show that the reliability of the scale was excellent for 3 constructs ranging from 0.780 (data skills) to 0.903 (decision-making). The data usage alpha is 0.499 which is well below 0.7 but it has been deemed acceptable as this is a low-risk study.

As discussed in Chapter 3, a high Cronbach's coefficient alpha shows higher reliability of the measurement scale (Cronbach, 1951). Nunnally and Bernstein (1994) recommend using alpha greater than 0.7. Field (2009) recommends retaining all values close to the overall alpha but deleting anything that is significantly greater.

4.4.1 Decision-Making

Table 4-8: Reliability Statistics for Decision-Making

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.903	.910	6

Source: (Based on online questionnaires, 2021)

The Cronbach Alpha of the decision-making construct is above 0.7 as suggested by Cronbach (1951). This scale is accepted as reliable and consistent.

4.4.2 Data Accessibility

Table 4-9: Reliability Statistics for Data Accessibility

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.883	.882	6

Source: (Based on online questionnaires, 2021)

The Cronbach Alpha of the data accessibility construct is .883 which deems it as reliable and consistent.

4.4.3 Data Skills

Table 4-10: Reliability Statistics for Data Skills

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.780	.817	3

Source: (Based on online questionnaires, 2021)

The data skills construct shows a Cronbach Alpha of .780 which indicates a reliable and consistent scale.

4.4.4 Data Usage

Table 4-11: Reliability Statistics for Data Usage

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.499	.497	3

Source: (Based on online questionnaires, 2021) – This table shows the results of the statistical tests run on the data.

Although the data usage construct is far lower than the recommended 0.7 indicating that it isn't a reliable scale a decision was taken to include it since this is a management study and the risk is low. It will be kept.

Composite scores were computed using averages to form the variables to be used for further analysis.

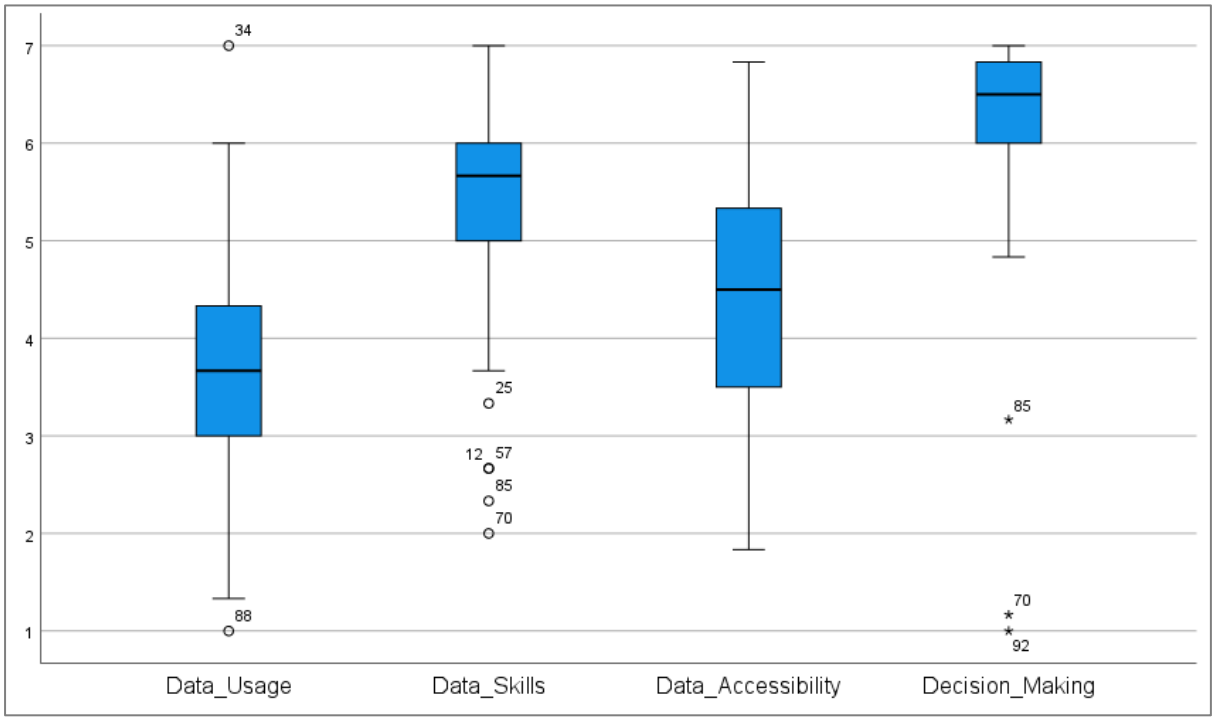
4.5 Assumption Testing

According to Field (2013) assumption testing is performed to prevent violations of rules. Linear correlation is reviewed to ensure that it is not too high as this would cause multicollinearity. It also looks for outliers. The data were therefore tested for the following assumptions: absence of outliers, normality, linearity, homogeneity of variance, independence of error terms, multicollinearity/collinearity, and normality of errors.

4.5.1 Outliers

Outliers are data points that are different from the data set; they are not within the range of most of the other observations. According to Field (2013) outliers can bias the estimate and magnify the sum of squared error. Tukey (1977) states that outliers fall outside the set boundaries of the interquartile range. The 'box and whiskers' plot is the most popular method that researcher use to detect outliers because they are simple to compute and understand (Iglewicz and Hoaglin, 1987). They were also available on SPSS and were thus adopted in this study.

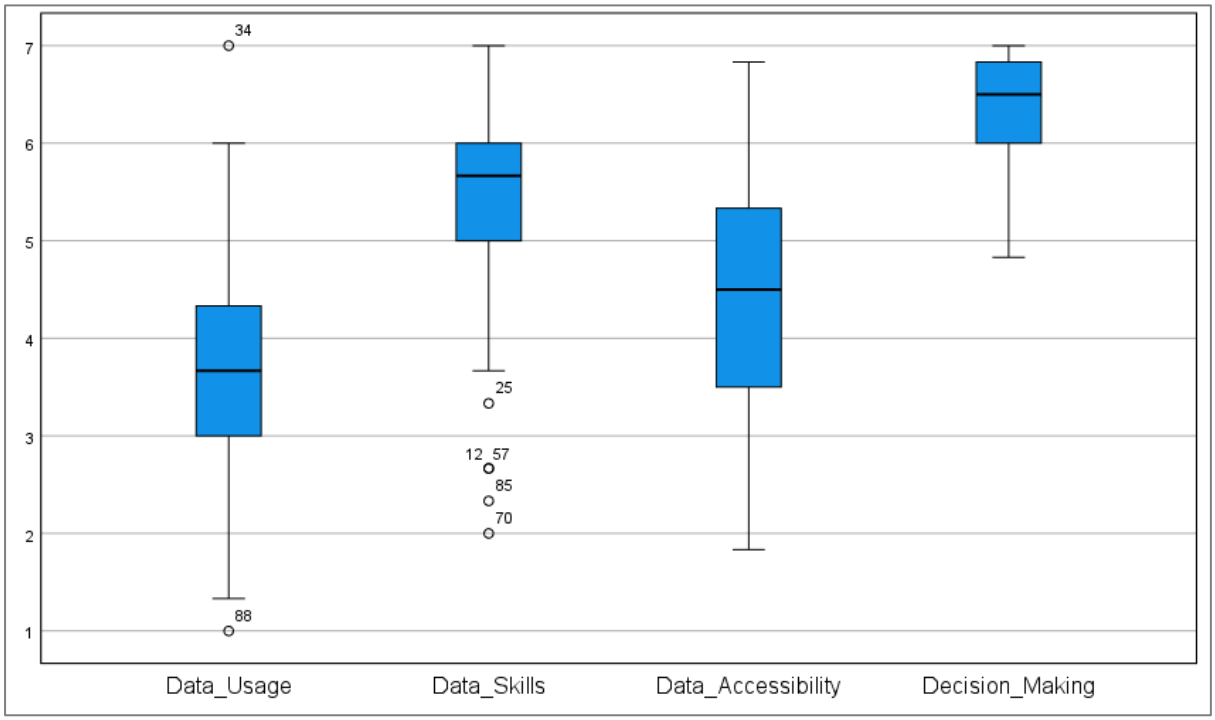
Figure 4-5: Boxplots with Outliers



Source: (Based on online questionnaires, 2021)

Figure 4-5 shows that there are 3 extreme values in the decision-making construct 92, 70, 85. Winsorizing was used to substitute the outliers to reduce the effect of them on the results, (Iglewicz and Hoaglin, 1987). The data was rerun with the substituted numbers and is reflected in Figure 4-6.

Figure 4-6: Boxplots with Outliers Addressed



Source: (Based on online questionnaires, 2021)

4.5.2 Normal Distribution

Most analysis requires that the data be roughly normally distributed to obtain generalisable results and correct inferences. There are a number of methods used to assess normality, but this study used kurtosis and skewness indices as recommended by Razali and Wah (2011). Field (2013) defines skewness as the symmetry and kurtosis as the peakedness/flatness of the distribution. He says that a normally distributed sample has a skewness and kurtosis close to zero. Cohen, Cohen, West, and Aiken (2013) suggest using a threshold of 2 for skewness and 7 for kurtosis. No problem of skewness and kurtosis were detected and therefore accepted that the data is normally distributed.

Table 4-12: Descriptive Statistics

	Range	Minimum	Maximum	Sum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Data Usage	6.00	1.00	7.00	443.33	3.6339	.10217	1.12849	1.273	.051	.219	.167	.435
Data Skills	5.00	2.00	7.00	670.62	5.4969	.09240	1.02062	1.042	-.883	.219	1.296	.435
Data Accessibility	5.00	1.83	6.83	531.00	4.3525	.10906	1.20456	1.451	-.173	.219	-.708	.435
Decision-Making	2.17	4.83	7.00	778.99	6.3852	.04821	.53252	.284	-1.015	.219	.741	.435
Valid N												

Source: (Based on online questionnaires, 2021)

4.5.3 Correlational Analysis (Linearity)

The purpose of the linearity test is to determine if there is a linear relationship between the dependent and independent variables. Tabachnick and Fidell (2003) found that linearity is a requirement for correlational and regression analysis. The Pearson Moment of Correlation was used to test the linearity of the study variables. Since none of the correlations in Table 4-13 were greater than 0.8, there was no multicollinearity. Field (2013) found that when correlations are higher than 0.8 or 0.9, variables in the model are highly correlated making it

difficult to determine the unique significance of each variable in the model. It produces misleading and unreliable regression results.

Table 4-13: Correlations

N =122		Data use	Data literacy	Data accessibility	Decision-making
Data Usage	Pearson Correlation	--			
	N	122			
Data Skills	Pearson Correlation	.051	--		
	Sig. (2-tailed)	.578			
	N	122	122		
Data Accessibility	Pearson Correlation	.158	.314**	--	
	Sig. (2-tailed)	.082	.000		
	N	122	122	122	
Decision-Making	Pearson Correlation	.162	.321**	.236**	--
	Sig. (2-tailed)	.075	.000	.009	
	N	122	122	122	122

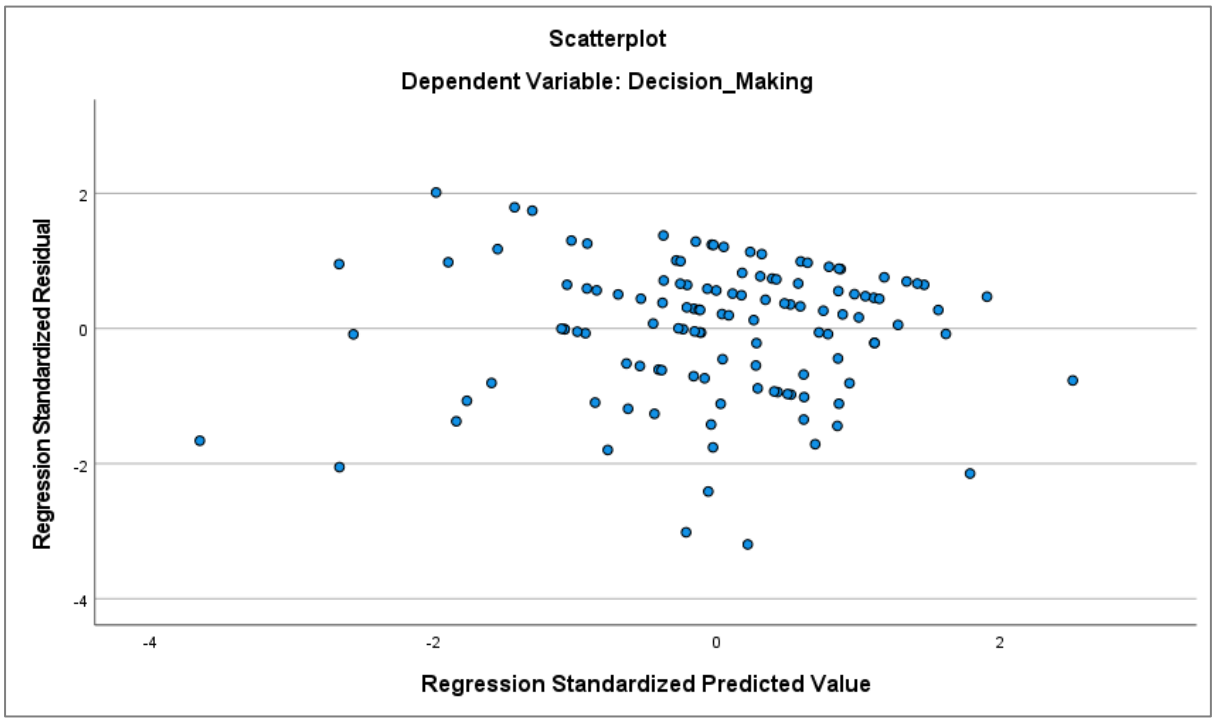
**. Correlation is significant at the 0.01 level (2-tailed).

Source: (Based on online questionnaires, 2021)

4.5.4 Homoscedasticity and Independent Errors

According to Field (2013), homoscedasticity is the homogeneity of variance. It is used to test grouped data. The residual plot is used to test for the ungrouped dataset. The violation of this assumption results in invalidating the confidence intervals and the significance tests (Field, 2013). Figure 4-7 shows that the residuals fall within -2 and 2 of the standard residuals cut-off. This indicates that the homoscedasticity assumption was not violated. The data is scattered evenly on the residual plot.

Figure 4-7: Scatterplot

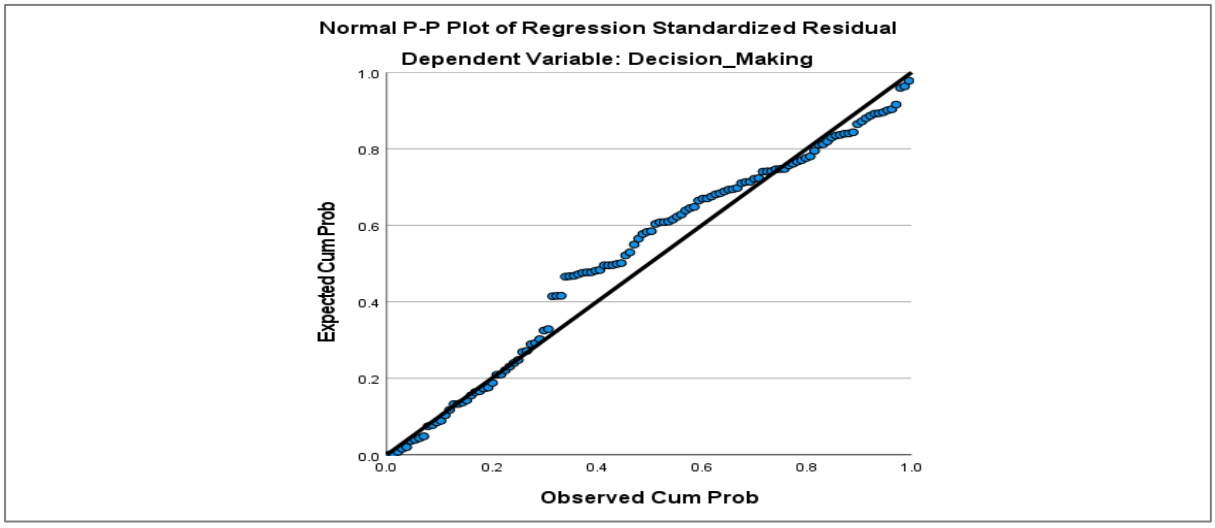


Source: (Based on online questionnaires, 2021)

4.5.5 Normal Errors

Errors should be normally distributed. An indication of this is when they are closer to the 45-degree line. Figure 4-8 shows that they are close to normality.

Figure 4-8: Normal P Plot of Regression Standardised Residual



Source: (Based on online questionnaires, 2021)

4.6 Regression Analysis

Table 4-14: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.373[a]	.139	.117	.50039	1.862

a. Predictors: (Constant), Data Accessibility, Data Usage, Data Skills

b. Dependent Variable: Decision - Making

Source: (Based on online questionnaires, 2021)

The model summary in Table 4-14 shows the results of the tests of the hypotheses. It illustrates how the predictors, also known as the independent variables, affect decision-making dependent variable. The R Square value indicates that all 3 values together explain 13.9% of what is happening in model or decision-making. This is an overall view of all variables acting together.

Table 4-15: ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	4.768	3	1.589	6.347	.001[b]
	Residual	29.545	118	.250		
	Total	34.313	121			

a. Dependent Variable: Decision Making

b. Predictors: (Constant), Data Accessibility, Data Usage, Data Skills

Source: (Based on online questionnaires, 2021)

Table 4-15 displays the ANOVA statistics. This shows whether the model is significant or not. It needs to be less than .05. The value is .001 which is less than 0.5 so the model is significant. It means that the model of Data usage, Data skills and Data accessibility is significant in explaining what is happening.

Table 4-16: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	5.133	.292		17.565	.000	4.554	5.711		
	Data Usage	.060	.041	.127	1.473	.143	-.021	.141	.975	1.026
	Data Skills	.143	.047	.273	3.036	.003	.050	.235	.901	1.109
	Data Accessibility	.058	.040	.130	1.431	.155	-.022	.137	.881	1.135

a. Dependent Variable: Decision-Making

Source: (Based on online questionnaires, 2021)

Table 4-16 breaks down the contribution of each of the variables. The standardised coefficients, also called beta, and the significance are the two important columns in this table. The beta value shows the extent to which the variable explains changes in the dependent variable and the significance will show how meaningfully it does that. Data Usage has a beta of .127 which means that it explains 12.7% changes in decision-making but a significance value of .143 tells us that this is not significant because it is greater than 0.05. The Data Skills variable has a beta of .273 which can be interpreted as explaining 27.3% of the changes in decision-making. This variable has a significance of .003, which is lower than 0.05 which makes it significant. Data Accessibility has a beta of .130 indicating that it explains 13% changes in the Decision-Making variable and is insignificant at .155.

4.7 Hypothesis Testing

H1: The use of data and analytics by senior management positively influence decision-making.

The results show that data usage influences decision-making, but the result is not significant.

H2: There is a positive relationship between data accessibility and decision-making.

The results show that there is a positive relationship between data accessibility and decision-making, but the result is not significant.

H3: Data skills positively influence decision-making.

The results show that data skills influence decision-making and is significant.

5 Discussion of the Research Findings

The objective of this chapter is to present the analysis and interpretation of the research results presented in the previous chapter. The findings of the study are discussed, and the empirical results are compared to the literature review presented in Chapter 2. The aim of the study is to evaluate the use of data and analytics by senior management in decision-making. The discussion and analysis will be addressed in two parts; firstly, it will delve into the general observations from the data collected. Secondly, it will be followed by the three research questions presented in Chapter 1.

5.1 General Observations from the Results

Decision-making – Some responses were removed from the analysis as the qualifying question of whether their role requires them to make decisions was answered negatively. 4% of the senior managers who responded said that they didn't make decisions in their current role, whilst 91% stated that the decisions that they make are important to the success of the organisation.

Data literacy – A large number of respondents (42%) felt that they needed additional training to be able to interpret the data available to them. The value in this is that they recognise the need to understand the data and the gap in their knowledge and skillset.

Data usage – A sizeable base (74%) responded that they rely on intuition and instincts when making decisions. This might represent an area for further investigation and might offer some insights into decision-making and data usage, as 100% of the respondents saw value in data-driven decision-making.

Data accessibility – 67% of respondents felt that they had access to all the data that they need to make decisions. This signifies an opportunity to solve the accessibility problem of the other 33%.

The next sections discuss the findings in relation to the research questions and the accompanying hypotheses. The three hypotheses, the findings and related literature and previous studies are individually detailed below.

5.2 Findings

5.2.1 The Relationship Between Data Usage and Data-Driven Decision-Making

The first research question asked, 'Is there a relationship between the use of data and analytics by senior management and data-driven decision-making?'

The empirical results show that the use of data and analytics positively influences data-driven decision-making. The alternate hypothesis was proven in this question as expected and is supported by findings in previous studies in this area. Constantiou and Kallinikos (2015) pointed out that managers are increasingly basing their decisions on insights generated from big data.

When decisions are made from an informed perspective, the result is an improvement in performance. This is borne out by Story, O'Malley, and Hart (2011) when they found that using data improves results. It also follows that when data is used to make decisions there is more creativity and innovation. This is confirmed by Ransbotham and Kiron (2017), who suggested that organisations find that data is a source of innovation.

These results are supported by Sharma, Mithas, and Kankanhalli (2014) who found that business value can be created through big data analytics. The strongest case for this is made by Chen and Zhang (2014) who stated that rich business intelligence enables better-informed business decisions.

Wamba, Gunasekaran, Akter, Ren, Dubey, and Childe (2017) further supports the above by adding that data-generated insights are relevant in organisations where making informed decisions is critical. Abbasi, Sarker, and Chiang (2016) added that the value of data in decision-making is increasing in importance.

Lycett (2013) adds that the use of this data results in managers making better decisions that are based on evidence rather than intuition or gut feel.

As managers see that the use of data and analytics in their decision-making results in more informed decisions, as well as increased improvement in results and performance, it will provide the impetus to continue referring to these sources when they make decisions. These managers will lead teams that see the value that data and analytics are adding. They will lead by example and thus create an environment that is data-led. In turn, this will create an organisation-wide data culture.

5.2.2 The Relationship Between Data Accessibility and Data-Driven Decision-Making

The second research question was, 'Is there a relationship between data accessibility by senior management and data-driven decision-making?' The alternate hypothesis that there is a positive relationship between data accessibility and data-driven decision-making was supported by the empirical evidence.

These findings were aligned with literature on this topic and previous studies on accessibility to data in decision-making. Gifford and Bobbit (1979) found that making analytical insights available when it is needed in a manner that is easy to access can help decision-makers yield better business results. Not having access to relevant or correct data creates a hurdle in decision-making.

Ranjan (2005) found that senior managers and other decision-makers in the organisation have a lot more information at their fingertips on which to base their decisions. Accessing this data easily and conveniently proves to be a major factor in using the data. Managers need to be able to know where the data can be found and how to access it. Lycett (2013) supports this by adding that advances in technology have led to massive increases in the volumes of data becoming available. Managers can often not sift through these to find what they require.

Barnaghi, Sheth, and Henson (2013) states that data security and privacy issues are additional factors that need to be considered when dealing with the topic of accessibility. Both data

security and privacy are currently important topics and are being addressed through data governance policies and practises.

These are important considerations and should inform the practises of any organisation that is expecting to lawfully use and store their customer's data to perform any type of analytics., e . Data security and privacy impact access to the data as only employees that comply and require access should be given access to it. This becomes a balancing act for the company as it considers who is allowed access and how to remain compliant with data security and privacy regulations.

Barbierato, Gribaudo, and Iacono (2014) propose that the challenge of inadequate infrastructure and insignificant data warehouse architecture are hindrances to proper management of accessibility to data. Barbierato et al. (2014) show that companies need to ensure that accessibility forms part of their data strategy planning. the

Though managers have more access to valuable data than ever before, the results are less clear when it comes to whether managers feel they have access to all the data they need to make critical business decisions. Gifford and Bobbit (1979) caution that access does not translate into understanding. This leads us to the discussion of the next variable – that of data literacy.

5.2.3 The Relationship Between Data Literacy and Data-Driven Decision-Making

According to this study, the last and arguably the most significant construct one in terms of its impact on data-driven decision-making, is data literacy. The research question put forward was, 'Is there a relationship between the data literacy of senior management and data-driven decision-making?'

The alternate hypothesis that there is a positive relationship between the data literacy of senior management and data-driven decision-making was proven in this study. The fact that being able to interpret and understand data and analytics is an essential factor in decision-making is supported by the literature. Kim, Trimi, and Chung (2014) found that one of the key

reasons why data investments do not show the expected dividends is a lack of properly skilled employees.

When building a data strategy, it is important that the right resources are deployed to execute the plan, (Davenport, 2006). He goes on to add that ensuring the right leadership increases the chances of success of any data project. Lycett (2013) suggests that managers need to have a deep and intuitive understanding to make decisions that generate value.

Sharma, Reynolds, Scheepers, Seddon, and Shanks (2010) explains that there are two parts to data literacy. The first concerns the way in which the data is relayed or presented to the audience and the second concerns the way in which that message is perceived or understood by the audience.

Potential value is lost when data analysts do not understand the business, or the business problem and the managers do not understand the analytical results. It results in a problematic gap between the ability of the organisation to produce analytical results and its ability to apply those results to business issues. The opportunity this presents is to nurture the skill of reading facts from figures, connecting them with the relevant decision-making process, and ultimately taking a data-driven business decision. The problem is exacerbated when an organisation's capacity to produce increasingly sophisticated analytics outpaces managers' abilities to understand these processes and make decisions based on these complex insights whilst not yet fully understanding it.

One suggestion offered by Taheri, Zomaya, Siegel, and Tari (2014) is that of data visualisation. It makes it easier to read and interpret because the data is graphically represented. This is one factor that helps the audience absorb the data quickly and easily and aids in understanding and interpreting the data.

The research has found that, if used appropriately, the technology that enables the storage and use of data as well as the capability of performing analytics can improve the decision-

making ability of senior managers. The aforementioned illustrates The Adaptive Structuration Theory, as established by DeSanctis and Poole (1994), in practise.

The findings of this study support the findings of Rice and Associates (1984) by showing that technology –, in this case the technology that enables data storage and processing – improves the ability of employees, and by extension the organisation, by enhancing efficiency, and productivity. However, further research is needed to establish whether it has an impact on satisfaction.

DeSanctis and Poole (1994) recommends The Adaptive Structuration Theory as an approach to studying the role that information technology plays in carrying out organisational change. The research findings of the research conducted support the choice of The Adaptive Theory as well as the findings of the other researchers reported on in the literature.

6 Summary, Conclusions, Limitations, and Recommendations

This chapter completes this research report by discussing the contribution of the study to the topic. It is followed by the conclusions reached and the limitations of the study. Some recommendations are proposed, and suggestions are made for future research.

6.1 Summary

The purpose of this study was to evaluate the use of data and analytics by senior managers in decision-making at a South African Pay-TV company. Essentially the most basic question being asked is if decisions are data-driven.

The significance of this study lies in its success at highlighting, through the empirical results and findings of this study, the importance of the three constructs of data usage, data literacy and data accessibility to data-driven decision-making. The findings will help the company, who have already made massive investments in their data and analytics infrastructure, realise greater value from these investments. It will provide a roadmap of areas to address to create a culture of data-driven decision-making.

6.2 Conclusions

Based on the results discussed in Chapter 4 and the findings presented in Chapter 5, the following conclusions can be drawn:

While the findings show that there is a positive relationship between data usage and data-driven decision-making, 74% of the managers surveyed still rely on intuition to make decisions. While this statistic is significant it also highlights an opportunity for improvement in driving data-driven decision-making for the organisation. There are several approaches that can be used to increase the usage of data and analytics. Because these require the access to systems and tools, as discussed in the previous part of the process, the usage can be measured and monitored, if implemented correctly. A suggested way of encouraging decision-makers to use the data would be creating simulation games through which the analysis and use of data can be practised. A vital part of getting this right is to include measuring data usage in the strategy

and implementation of the accessibility component of this process. If usage can be measured, decision-makers can be rewarded for high usage of the data and the analytics available to them. The findings of the study highlight a few areas of opportunity for improvement and thereby creating a data-driven culture. The first finding, which ties into the plan detailed above, is one that has been identified by the decision-makers themselves. The study shows that 42% of respondents know that they need further training to be able to interpret the data. Another opportunity identified is that of improved accessibility. Of the respondents, 33% indicated that they do not have access to the data that they need to base their decisions on. Finally, although 100% of respondents know that there is value in making data-driven decisions, 74% still rely on their intuition to make decisions. These are immediately addressable opportunities for the organisation and the researcher is of the opinion that a relatively small number of adjustments can make a significant impact in a short period of time.

6.3 Limitations

This study was limited to the senior management team currently employed at the South African Pay-TV company. It excluded the executives as well as junior managers. To enable more insights on decision-making at the different levels of management the study could be expanded to include all levels of management.

The primary researcher is a senior manager of the business unit that provides data and analytics to some of the respondents in the sample. Although confidentiality was ensured it is possible that the fact that the primary researcher is thus employed might have affected the responses received. This bias could be addressed by utilising the services of an independent research firm to carry out the research.

An online questionnaire was used due to the restrictions of the Coronavirus pandemic that has led to most respondents having to work from home. The convenience and ease of using this type of survey did assist in getting a significant sample size. Face-to-face interviews or telephonic interviews is a possible way to address this issue if time allows.

6.4 Recommendations

The recommendations proposed are based on the findings of this study and the conclusions drawn, based on these.

Since the most significant construct to driving data-driven decision-making was data literacy skills, it is proposed that The South African Pay-TV company Group incorporate training in this area for all management and decision-makers.

An awareness drive that takes the form of knowledge-sharing sessions that highlights what data and analytics are available and that stimulates the use of these is recommended.

Lastly, it is an imperative that all decision-makers have access to the data and analytics that they need to enable data-driven decision-making culture. Choosing and implementing the correct tools and technologies is a very important part of designing the correct data strategy. Developing a leadership that understands the importance of implementing and supporting the strategy should form part of the data strategy. Talent management, which encompasses hiring and retaining staff with the right skills, is an imperative. Aligning these three components is key to executing a successful data strategy.

A three-pronged approach is recommended. The order of implementation is vital to the success of this plan, as one construct is dependent on the next. It can be likened to building a solid foundation.

Data literacy should be addressed first. Key personnel should be identified and equipped with the right skills. Suggested skills include learning how to interpret the existing data and analytics within the organisation. These employees should be shown how to read graphs, interpret data, and understand numerical and statistical data.

The end goal is to train and arm senior management and key decision-makers with the correct skills to the data and analytics produced within the organisation.

The learning of data skills cannot be a once-off exercise if the goal is to create a data-driven culture. To remain relevant in the age of big data, training must be an ongoing process which will ensure that managers remain informed of technological progress and have the tools to apply it.

The issue of accessibility should be addressed next. Granting access to the right people, the right data, at the right time is key. A crucial step in the process is identifying what data there is and who needs access to it. Regulations around privacy and storage of personal data complicates the matter and the company must have strict measures and policies in place to monitor this.

Controls need to be in place to ensure that only qualifying employees are accessing the data. Initially, this is an intensive process to develop but once it is in place, the process is less intensive to maintain.

Data governance is a component of accessibility as it ensures that the correct definitions and measures are in place to ensure that the data is used and interpreted correctly. This illustrates why ensuring sufficient data literacy should precede addressing the issue of accessibility.

The final step requires the greatest change management - the actual use of the available data and analytics. The access to, use of and correct interpretation of the data in decision-making should be encouraged by top-tier leadership within the company.

The research referenced within this paper has shown how companies in other industries have seen improvement in performance and have been outperforming their competitors, once they have the correct data strategies in place. If the plan, as detailed above, is implemented the organisation will be able to operate successfully within the age of data and the evolving technologies that drives it.

6.5 Areas for Future Research

This study was limited to senior managers in the organisation but there would be value in extending its reach to include junior managers. A comparative study could be done between junior and senior managers to measure the difference in their decision-making approaches and how they use data.

Research could also be done to ascertain whether improved data literacy earlier in one's career could have a greater impact on decision-making. A longitudinal study that contrasts and quantifies its impact of data literacy training on junior managers as opposed to those who do not could provide insight into what drives data-driven decision-making. This would add value to companies who have large investments in data and analytics but who are not seeing the benefit of this spend.

The research could also be extended to include other companies in the same industry. This could lead to a better understanding of what the industry benchmark is. A comparison could be made with improvements in performance as seen in other industries.

Such a future study observes companies that have their usage tracking strategies in place, and compare users versus non- or low-users of dashboards, reports and other analytics and data available to senior managers. This is a way to verify the findings of this report. The outcome of such studies will be useful to organisations to help identify areas of improvement and programmes that might help senior managers make data-driven decisions.

The final recommendation concerns the topic of visualisations and storytelling and how these feed into how the audience receive the information.

Data storytelling and visualisations are of importance right now and more companies are placing value on this. Using storytelling with data training and how to present your data in way that is understood by your audience will address the rise of this area of data analytics.

This will approach the topic of this research paper from a different perspective. The recommendation is to look at the person preparing and presenting the data and analytics rather than focussing on the consumers of that data, such as the senior managers that we interviewed in this study.

As data and analytics become increasingly valuable to organisations there will be many opportunities to delve into this area of research from an academic perspective which, in turn, can create real-world opportunities for improvement.

7 References

1. Abbasi, A., Sarker, S., and Chiang, R. H. (2016). Big data research in information systems: Toward an inclusive research agenda. Journal of the Association for Information Systems, 17(2).
2. Allmendinger, G. and Lombreglia, R. (2005). Four Strategies for the Age of Smart Services. Harvard Business Review, 83(10), 131-145.
3. Ambrosini, V., and Bowman, C. (2009). What are dynamic capabilities and are they a useful construct in strategic management? International Journal of Management Reviews, 11(1), 29–49.
4. AMR Research (2008). Spending on Business Intelligence and Performance Management to Top $57.1B in 2008. Retrieved from http://www.amrresearch.com/Content/View.asp?pmillid=21481 (viewed Jan 2009).
5. Aral, S. and Weill, P. (2007). IT Assets, Organisational Capabilities and Firm Performance: How Resource Allocations and Organisational Differences Explain Performance Variation. Organisation Science, 18(5), 1-18.
6. Arnott, D. (2004). Decision Support Systems Evolution: Framework, Case Study and Research Agenda. European Journal of Information Systems, 13(4), 247-259.
7. Banerjee, A., Bandyopadhyay, T., and Acharya, P. (2013). Data analytics: hyped up aspirations or true potential. Vikalpa. The Journal for Decision Makers, 38(4), 1–11.
8. Banker, S. (2014). Amazon and anticipatory shipping: A dubious patent? Forbes. Retrieved January 24, 2021, from http://www.forbes.com/sites/stevebanker/2014/01/24/amazon-and-anticipatory-shipping-a-dubious-patent/.
9. Barbierato, E., Gribaudo, M., and Iacono, M. (2014). Performance evaluation of NoSQL bigdata applications using multi-formalism models. Future Generation Computer Systems, 37, 345–353.
10. Barnaghi, P., Sheth, A., and Henson, C. (2013). From data to actionable knowledge: big data challenges in the web of things. IEEE Intelligent Systems, 28(6), 6–11
11. Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.
12. Barney, J. B. (2014). Howmarketing scholars might help address issues in resource-based theory. Journal of the Academy of Marketing Science, 42(1), 24–26.
13. Bell, E., Bryman, A., and Harley, B. (2018). Business Research Methods (5 ed.): Oxford University Press.
14. Berners-Lee, T., and Shadbolt, N. (2011). There's gold to be mined from all our data. The Times, London 1:1–2. Retrieved April 21, 2021, from http://www.thetimes.co.uk/tto/opinion/columnists/article3272618.
15. Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., and Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. Management Information Systems, 37(2), 471–482.
16. Bhattacherjee, A., 2012. Social science research: principles, methods, and practices.
17. Bihani, P., and Patil, S. T. (2014). A comparative study of data analysis techniques. International Journal of Emerging Trends and Technology in Computer Science, 3(2), 95–101.

18. Bloomberg Businessweek. (2011). The Current State of Business Analytics: Where Do We Go from Here? Bloomberg Businessweek Research Services. Retrieved from http://www.sas.com/resources/asset/ busanalyticsstudy_wp_0823201 1 .pdf
19. Bolarinwa, O. A. (2015). Principles and methods of validity and reliability testing of questionnaires used in social and health science researches. Niger Postgrad Med J 22:195-201. Retrieved from: https://www.npmj.org/text.asp?2015/22/4/195/173959.
20. Braganza, A., Brooks, L., Nepelski, D., Ali, M. and Moro, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. Journal of Business Research, 70, 328-337.
21. Brains, C., Willnat, L., Manheim, J. and Rich, R. (2011). Empirical Political Analysis 8th edition. Boston: Longman.
22. Brannen, J. (2016). Mixing Methods: Qualitative and Quantitative Research. New York, USA: Routledge - Taylor and Francis Group.
23. Brown, B., Chui, M., and Manyika, J. (2011). Are you ready for the era of Big Data? The McKinsey Quarterly, 4, 24–35.
24. Bryman, A. (1992). 'Quantity and Quality in Social Research'. Routledge: London and New York.
25. Bryman, A. (2012). Social Research Methods (4th ed.): Oxford University Press.
26. Bryman, A. (2015). Social research methods: Oxford university press.
27. Carr, D. (2013). Giving viewers what they want. New York Times, 2013, B1.
28. Carte, T., Schwarzkopf, A., Shaft, T. and Zmud, R. (2005). Advanced Business Intelligence at Cardinal Health. MIS Quarterly Executive, 4(4), 413-424.
29. Caruana, A., and Fenech, N. (2005). The effect of perceived value and overall satisfaction on loyalty: A study among dental patients. Journal of Medical Marketing: Device, Diagnostic and Pharmaceutical Marketing, 5(3), 245-255.
30. Cavana, R. Y., Delahaye, B. L., and Sekaran, U. (2001). Applied business research: Qualitative and quantitative methods. John Wiley and Sons Inc.
31. Chang, C.-W., Tseng, T.-H., and Woodside, A. G. (2013). Configural algorithms of patient satisfaction, participation in diagnostics, and treatment decisions' influences on hospital loyalty. Journal of Services Marketing, 27(2), 91-103.
32. Chen, D. Q., Preston, D. S., and Swink, M. (2015) How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. Journal of Management Information Systems, 32(4), 4-39, DOI: 10.1080/07421222.2015.1138364.
33. Chen, H., Chiang, R. H., and Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. MIS Quarterly, 36(4), 1165-1188. Retrieved from https://www.jstor.org/stable/41703503.
34. Chen, J., Chen, Y., Du, X., Li, C., Lu, J., Zhao, S., and Zhou, X. (2013). Big data challenge: a data management perspective. Frontiers of Computer Science, 7(2), 157–164.
35. Chen, M., Mao, S., and Liu, Y. (2014). Big Data: a survey. Mobile Networks and Applications, 19(2), 171–209.
36. Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2013). Applied multiple regression/correlation analysis for the behavioral sciences: Routledge.
37. Constantiou, I. D., and Kallinikos, J. (2015). New games, new rules: Big data and the changing context of strategy. Journal of Information Technology, 30(1), 44–57.

38. Cooper, D. R., Schindler, P. S., & Sun, J. (2006). Business research methods.
39. Creswell, J. W., (2013). Research design: Qualitative, quantitative, and mixed methods approaches. Sage publications.
40. Creswell, J. W. (2014) Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. 4th edn. Sage Publications, Inc.
41. Creswell, J. W. (2017). Research Design, Qualitative, Quantative and Mixed research approaches. Nebraska: Sage.
42. Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. psychometrika, 16(3), 297-334. Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. Psychological bulletin, 52(4), 281.
43. D'Aveni, R. A., Dagnino, G. B., and Smith, K. G. (2010). The age of temporary advantage. Strategic Management Journal, 31(13), 1371–1385.
44. Davenport, T. H. (2006). Competing on Analytics. Harvard Business Review, (4(1), 98-107.
45. Davenport, T. H., and Dyché, J. (2013). Big data in big companies. International Institute for Analytics. Retrieved from http://www.demonish.com/cracker/1431316877_1217a9641e/bigdata-bigcompanies-106461.pdf.
46. Davenport, T. H., and Harris, J. G. (2007). Competing on analytics: The new science of winning. Harvard Business Press.
47. Davenport, T. H., Barth, P., and Bean, R. (2012). How big data is different. MIT Sloan Management Review, 54(1), 43–46.
48. Davenport, T. H. and Patil, D. J. (2012). Data scientist. Harvard Business Review, 90(5), 70-76.
49. Day, G. S. (2014). An outside-in approach to resource-based theories. Journal of the Academy of Marketing Science, 42(1), 27–28.
50. DeSanctis, G., and Poole, M. S. (1994). Capturing the Complexity in Advanced Technology Use: Adaptive Structuration Theory. Organization Science, 5(2), 121-147. doi:1047-7039/94/0502/0121.
51. Eisenhardt, K. M. and Martin, J.A. (2000). Dynamic Capabilities: What Are They? Strategic Management Journal, 22, 1105-1121.
52. Ellis, K. (2009). Business Analysis Benchmark 2009: The Pass to Success. IAG Consulting.
53. Erevelles, S., Fukawa, N., and Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. Journal of Business Research, 69(2), 897–904. doi: 10.1016/j.jbusres.2015.07.001.
54. Etikan, I., Musa, S. A., and Alkassim, R. (2016). Comparison of Convenience Sampling and Purposive Sampling. American Journal of Theoretical and Applied Statistics, 5(1), 1.
55. Fayyad, U., Piatetsky-Shapiro, G., and Smyth, P. (1996). From data mining to knowledge discovery in databases. AI Magazine, 17(3), 37–53.
56. Field, A. (2009). Discovering statistics using SPSS: Sage publications.
57. Field, A. (2013). Discovering statistics using IBM SPSS statistics (4th Edition ed.): Sage.
58. Friedrich, O., Stoler, P. Moritz, M., and Nash, J. N. (1983). Machine of the year: The computer moves in. Time Magazine, 121(1), 14–28.
59. Gandomi, A., and Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, 35(2), 137–144.

60. Gartner. (2008). Australian and New Zealand CIOs Expect Lower Than Average IT Budget Growth in 2008. Retrieved from http://www.gartner.com/it/page.jsp?id=606007 (viewed Jan 2009).
61. Gattiker, T. and Goodhue, D. (2005). What happens after ERP implementation: How interdependence and differentiation affect plant level outcomes. MIS Quarterly, 29(3), 561-587.
62. Gavetti, G. (2005). Cognition and Hierarchy: Rethinking the Micro-foundations of Capabilities' Development. Organisation Science, 16(6), 599-686.
63. Günther, W. A., Mehrizi, M. H. R., Huysman, M., and Feldberg, F. (2017). Debating big data: A literature review on realising value from big data. The Journal of Strategic Information Systems, 26(3), 191–209.
64. Gupta, M. and George, J. F. (2016). Toward the development of a big data analytics capability. Information and Management 53(8), 1049-1064.
65. Heale, R. and Twycross, A. (2015). Validity and reliability in quantitative studies. Evidence-Based Nursing, 18:66-67. Retrieved from http://dx.doi.org/10.1136/eb-2015-102129.
66. Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2010). Multivariate data analysis: A global perspective.
67. Hamm, S. (2009). IBM Roars into Business Consulting. Business Week Online.
68. Harrington, S. J., 1996. The effect of codes of ethics and personal denial of responsibility on computer abuse judgments and intentions. MIS quarterly, pp.257-278.
69. Helfat, C.E., Finkelstein, S., Mitchell, W., Peteraf, M.A., Singh, H., Teece, D.J., and Winter, S.G. (2007). Dynamic Capabilities: Understanding Strategic Change in Organisations. Carlton: Blackwell.
70. Ismail, K., and Zainuddin, S. (2013). Research Paradigms for Accounting: A Review. Asian Journal of Accounting Perspectives, 50-56.
71. Iglewicz, B., & Hoaglin, D. C. (1987). Use of boxplots for process evaluation. Journal of Quality Technology, 19(4), 180-190.
72. Jiang, H., Chen, Y., Qiao, Z., Weng, T. H., and Li, K. C. (2015). Scaling up Map Reduce-based big data processing on multi-GPU systems. Cluster Computing, 18(1), 369–383.
73. Joseph, R. C., and Johnson, N. A. (2013). Big data and transformational government. IT Professional, 15(6), 43–48.
74. Jukić, N., Sharma, A., Nestorov, S., and Jukić, B. (2015). Augmenting data warehouses with Big Data. Information Systems Management, 32(3), 200–209.
75. Kaisler, S., Armour, F., Espinosa, J.A. and Money, W. (2013). Big data: Issues and challenges moving forward. System sciences (HICSS), 46, 995-1004.
76. Kalof, L., Dan, A., and Dietz, T. (2008). Essentials of Social Research. New York: Open University Press.
77. Kim, G. H., Trimi, S., and Chung, J. H. (2014). Big-data applications in the government sector. Communications of the ACM, 57(3), 78–85.
78. King, N., and Ryan, B. J. (2019). The Impact of Social Inclusion on the Social Development of Students with a General Learning Difficulty in Postprimary Education in Ireland. Education Research International, 2019, 1-7. doi:10.1155/2019/6327567
79. Kiron, D. (2017). Lessons from becoming a data-driven organisation. MIT Sloan Management Review, 58(2).

80. Kohavi, R., Rothleder, N., and Simoudis, E. (2002). Emerging Trends in Business Analytics. Communications of the ACM, 45(8), 45-48.
81. Kohli, R. (2007). Innovating to Create IT-Based New Business Opportunities at United Parcel Service. MIS Quarterly Executive, 6(4), 199-210.
82. Kozlenkova, I. V., Samaha, S. A., and Palmatier, R. W. (2014). Resource-based theory in marketing. Journal of the Academy of Marketing Science, 42(1), 1–21.
83. Kumar, A., Niu, F., and Ré, C. (2013). Hazy: making it easier to build and maintain big-data analytics. Communications of the ACM, 56(3), 40–49.
84. Kunc, M. H., and Morecroft, J. D. W. (2010). Managerial decision making and firm performance under a resource-based paradigm. Strategic Management Journal, 31(11), 1164–1182.
85. Lee, R. P., and Grewal, R. (2004). Strategic responses to new technologies and their impact on firm performance. The Journal of Marketing, 68(4), 157–171.
86. Leedy, P. D., and Ormrod, J. E. (2015). Practical research: Planning and design. Upper Saddle River, New Jersey: Pearson Education Inc.
87. Lin, Y., and Wu, L. Y. (2014). Exploring the role of dynamic capabilities in firm performance under the resource-based view framework. Journal of Business Research, 67(3), 407–413.
88. Lycett, M. (2013). 'Datafication': Making sense of (big) data in a complex world. European Journal of Information Systems, 22(4), 381–386.
89. Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., and Byers, A. H. (2011). Big Data: The Next Frontier for Innovation, Competition, and Productivity. McKinsey Global Institute. Retrieved from (http://www.mckinsey.com/insights/mgi/research/technology_and_innovation/big_data_the_next_frontier_for_innovation.
90. Marzooqi, O. A. (2015). Impact of Different Factors on Organisational Productivity International Journal of Sales, Retailing and Marketing, 4(8).
91. Mayer-Schönberger, V., and Cukier, K. (2013). Big data: A revolution that will transform how we live, work, and think. New York: Houghton Mifflin Harcourt.
92. McAfee, A. and Brynjolfsson, E. (2012). Big data: The management revolution. Harvard Business Review, 90(10), 60–68. Retrieved from https://hbr.org/2012/10/big-data-the-management-revolution.
93. McNabb, D. E. (2015). Research Methods for Political Science: Quantitative and Qualitative Methods: Taylor and Francis.
94. Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019). Big data analytics and firm performance: Findings from a mixed-method approach. Journal of Business Research, 98(C), 261-276. Retrieved from https://ideas.repec.org/a/eee/jbrese/v98y2019icp261-276.html.
95. Mikalef, P., Framnes, V. A., Danielsen, F., Krogstie, J., and Olsen, D. H. (2017). Big data analytics capability: antecedents and business value. Paper presented at the Pacific Asia Conference on Information Systems 2017 Proceedings. 136. Retrieved from http://aisel.aisnet.org/pacis2017/136.
96. Mikalef, P., Pappas, I. O., Krogstie, J., and Giannakos, M. (2017). Big data analytics capabilities: A systematic literature review and research agenda. Information Systems and e-Business Management, 1–32.
97. Mithas, S., Lee, M. R., Earley, S., and Murugesan, S. (2013). Leveraging big data and business analytics. IT Professional, 15(6), 18–20.

98. Neuman, W. L. (2013) Social Research Methods: Qualitative and Quantitative Approaches. 7th edn. Harlow: Pearson Education Limited. doi: 10.2307/3211488.
99. Nevo, S., and Wade, M.R. (2010). The Formation and Value of IT-Enabled Resources: Antecedents and Consequences of Synergistic Relationships. MIS Quarterly, 34(1), 163-183.
100. Nunnally, J. (1978). Psychometric methods: New York: McGraw-Hill
101. Nunnally, J. C., & Bernstein, I. H. (1994). Psychological theory. New York, NY: MacGraw-Hill.
102. Nyce, C. and Cpcu, A. (2007). Predictive analytics white paper. American Institute for CPCU. Insurance Institute of America, 9-10.
103. Opie, C., and Brown, D. (2019). Getting Started in Your Educational Research: Design, Data Production and Analysis: SAGE Publications.
104. Oracle (2012). Big data for the enterprise. OracleWhite Paper, 1–14. Retrieved from http://www.oracle.com/us/products/database/big-data-forenterprise-519135.pdf.
105. Pappas, I. O., Mikalef, P., Giannakos, M. N., Krogstie, J., and Lukaku's, G. (2018). Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. 16(3), 479–491.
106. Pfeffer, J. and Sutton, R. (2006). Evidence-based management. Harvard Business Review, 84(1), 62-68.
107. Piccoli, G. and Watson, R. (2008). Profit from Customer Data by Identifying Strategic Opportunities and Adopting the 'Born Digital' Approach. MIS Quarterly Executive, 7(3) 113-122.
108. Popovič, A., Hackney, R., Tassabehji, R., and Castelli, M. (2018). The impact of big data analytics on firms' high value business performance. Information Systems Frontiers, 20(2), 209–222.
109. PwC. Capitalising on the promise of big data. 2013.
110. Raghupathi, W., and Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. Health information science and systems, 2(1), 3.
111. Rahi, S. (2017). Research Design and Methods: A Systematic Review of Research Paradigms, Sampling Issues and Instruments Development. International Journal of Economics and Management Sciences, 6(2), 1-5. doi: 10.4172/2162-6359.1000403.
112. Ransbotham, S., Kiron, D., Prentice, P. K. (2015) Minding the analytics gap. MIT Sloan Manag Rev 56(3):63.
113. Ransbotham, S., and Kiron, D. (2017). Analytics as a source of business innovation. MIT Sloan Management Review, 58(3), 1–16.
114. Razali, N. M., & Wah, Y. B. (2011). Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-darling tests. Journal of statistical modelling and analytics, 2(1), 21-33.
115. Remenyi, D. and Williams, B. (1993a) Some aspects of methodology for research in information systems, University of the Witwatersrand, Department of Information Systems: Working Paper Series No. 002, 3rd March.
116. Rice, R., and Associates. (1984). The New Media: Communication, Research, and Technology. Beverly Hills, CA: Sage Publications.
117. Ritson, M. (2014). Amazon has seen the future of predictability. Marketing Week. Retrieved from http://www.marketingweek.co.uk/opinion/ritson/amazon-has-seen-the-future-of-predictability/4009154.article.

118. Sambamurthy, V., Bharadwaj, A., and Grover, V. (2003). Shaping Agility through Digital Options: Reconceptualising the Role of Information Technology in Contemporary Firms. MIS Quarterly, 27(2), 237-263.
119. Sandhu, R., and Sood, S. K. (2014). Scheduling of big data applications on distributed cloud based on QoS parameters. Cluster Computing, 18, 1–12.
120. Satell, G. (2014). 5 things managers should know about the big data economy. Forbes. Retrieved from http://www.forbes.com/sites/gregsatell/2014/01/26/5-things-managers-should-know-about-the-big-data-economy/.
121. Saunders, M., Lewis, P. and Thornhill, A. (2009). Research Methods for Business Students. Prentice Hall: London.
122. Seddon, J.J. and Currie, W.L. (2017). A model for unpacking big data analytics in high-frequency trading. Journal of Business Research, 70, 300-307.
123. Seddon, P., Calvert, C. and Yang, S. (2010). A multiproject model of key factors affecting organisational benefits from enterprise systems. MIS Quarterly, 32(2), 305-328.
124. Sekaran, U. and Bougie, R. (2013) Research Methods for Business: A Skill-Building Approach.
125. Shanks, G., and Sharma, R. (2011). Creating value from business analytics systems: the impact of strategy. 15th Pacific Asia Conference on Information Systems: Quality Research in Pacific, PACIS 2011, 1-12. Queensland: Queensland University of Technology. Retrieved from https://ro.uow.edu.au/infopapers/3817/.
126. Shanks, G., Bekmamedov, N. and Sharma, R. (2011). Creating value from business analytics systems: a process-oriented theoretical framework and case study. 22nd Australasian Conference on Information Systems, 1-10.
127. Shanks, G., Sharma, R, Seddon, P. and Reynolds, P. (2010). The Impact of Strategy and Maturity on Business Analytics and Firm Performance: A Review and Research Agenda. Proc. 21st Australasian Conference on Information Systems, QUT, Brisbane, December.
128. Sharma, R., Mithas, S., and Kankanhalli, A. (2014). Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations. European Journal of Information Systems, 23(4), 433–441.
129. Sharma, R., Reynolds, P., Scheepers, R., Seddon, P., and Shanks, G. (2010). Business Analytics and Competitive Advantage: A Review and a Research Agenda. Bridging the Socio-Technical Gap in DSS - Challenges for the Next Decade, 187-198.
130. Sivarajah U., Kamal M. M., Irani Z., and Weerakkody, C. (2017). Critical analysis of Big Data challenges and analytical methods. Journal of Business Research, 70, 263-286. Retrieved from https://www.sciencedirect.com/science/article/pii/S014829631630488X.
131. Smith, M. (2017). Research methods in accounting. Retrieved from https://s3.amazonaws.com/academia.edu.documents/37862035/Research_Methods_in_Accounting_Malcolm_Smith.pdf?AWSAccessKeyId=AKIAIWOWYYGZ2Y53104UL3AandExpires=1543261809andSignature=IEuqsDee8mp8ZNqIs%2FsBRYVtnQ0%3Dandresponse-content-disposition=inline%3B%20filename%3Dmetlit.pdf.
132. Smith, S. V. (2013). What's behind the future of hit movies? An algorithm. Marketplace (Retrieved 1st December 2014 from http://www.marketplace.org/topics/business/whats-behind-future-hit-movies-algorithm).

133. Story, V., O'Malley, L., and Hart, S. (2011). Roles, role performance, and radical innovation competencies. Industrial Marketing Management, 40(6), 952–966.
134. Strang, K. D. (2015). Why Practitioner-Scholars Need a Research Design Typology: Palgrave Macmillan, New York.
135. Sukamolson, S. (2007). Fundamentals of quantitative research. Language Institute Chulalongkorn University, 1-20.
136. Sultana, S., Zulkifli, N., and Zainal, D. (2018). Environmental, Social and Governance (ESG) and Investment Decision in Bangladesh. Sustainability, 10(6), 1-19.
137. Sumaedi, S., Gede Mahatma Yuda Bakti, I., Rakhmawati, T., J. Astrini, N., Widianti, T., and Yarmen, M. (2014). The empirical study on patient loyalty: the role of trust, perceived value, and satisfaction (a case study from Bekasi, Indonesia). Clinical Governance: An International Journal, 19(3), 269-283.
138. Szongott, C., Henne, B., and von Voigt, G. (2012). Big data privacy issues in public social media. 6th IEEE international conference on digital ecosystems technologies (DEST). 1–6.
139. Tabachnick, B. G., & Fidell, L. S. (2003). Using multivariate statistics (Sixth Edition ed.). Pearson.
140. Taherdoost, H. (2016). Validity and Reliability of the Research Instrument; How to Test the Validation of a Questionnaire/Survey in a Research). Retrieved from SSRN: https://ssrn.com/abstract=3205040 or http://dx.doi.org/10.2139/ssrn.3205040.
141. Tukey, J. W. (1977). Exploratory data analysis.
142. Taheri, J., Zomaya, A. Y., Siegel, H. J., and Tari, Z. (2014). Pareto frontier for job execution and data transfer time in hybrid clouds. Future Generation Computer Systems, 37, 321–334.
143. Teece, D.J., Pisano, G., and Shuen, A. (1997). Dynamic Capabilities and Strategic Management. Strategic Management Journal, 18(7), 509-533.
144. Theofanidis, D., and Fountouki, A. (2018). Limitations and Delimitations in the Research Process. Perioperative nursing (GORNA), 7(3), 155-162. doi:10.5281/zenodo.2552022.
145. Tongco, M. D. C. (2007). Purposive Sampling as a Tool for Informant Selection. Ethnobotany Research and Applications, 5(1), 147-158.
146. Van de Ven, A.H. and Poole, M.S. (1995). Explaining Development and Change in Organisations. Academy of Management Review, 20, 510-540.
147. Vidgen, R., Shaw, S. L., and Grant, D. B. (2017). Management challenges in creating value from business analytics. European journal of operational research, 261(2), 626-639. https://doi.org/10.1016/j.ejor.2017.02.023.
148. Wade, M. and Hulland, J. (2004). The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research. MIS Quarterly, 28(1), 107-142.
149. Waller, M. A., and Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. Journal of Business Logistics, 34(2), 77–84.
150. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., and Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365.

151. Wang, G., Gunasekaran, A., Ngai, E. W., and Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98–110.
152. Watson, H. J. (2014). Tutorial: big data analytics: Concepts, technologies, and applications. Communications of the Association for Information Systems, 34(1), 1247–1268.
153. Weill, P., and Ross, J.W. (2009). IT savvy: What top executives must know to go from pain to gain. Harvard Business Press.
154. Weiner, J. (2007). Measurement: reliability and validity measures. Bloomberg School of Public Health, Johns Hopkins University. Retrieved from http://ocw. jhsph. edu/courses/hsre/PDFs/HSRE_lect7_weiner. pdf. http://jae. oxfordjournals. org.
155. Wixom, B.H. and Watson, H.J. (2001) An empirical investigation of the factors affecting data warehousing success. MIS Quarterly 25(1), 17-41.
156. Wotela, K. (2017). Towards an Outcomes-Based Approach to a 'Research Strategy, Design, Procedure and Methods' Chapter for Business and Public Administration Research. Journal of Public Administration, 52(1.1), 223-246.
157. Wu, L. Y. (2010). Applicability of the resource-based and dynamic-capability views under environmental volatility. Journal of Business Research, 63(1), 27–31.
158. Yi, X., Liu, F., Liu, J., and Jin, H. (2014). Building a network highway for big data: architecture and challenges. IEEE Network, 28(4), 5–13.
159. Zhang, F., Liu, M., Gui, F., Shen, W., Shami, A., and Ma, Y. (2015a). A distributed frequent itemset mining algorithm using Spark for Big Data analytics. Cluster Computing, 18(4), 1493–1501.
160. Zikmund, W. G., Babin, B. J., Carr, J. C., and Griffin, M. (2013). Business Research Methods (8th ed.): South-Western College Pub.

8 Appendix A: Research Data Collection Instrument

The Use of Data and Analytics an Strategic Decision-Making an a South African Pay-TV Company

Start of Block: Block 1

Q1.1
You are invited to complete a survey questionnaire that forms part of my formal qualification for Master of Business Administration at Wits Business School.

The title of this study is: The use of data and analytics in strategic decision-making in a South African Pay-TV company.

The research is purely for academic purposes and it will take you no more than 5 minutes to complete.

Your responses will be kept strictly confidential and anonymous.

Your participation is greatly appreciated.

End of Block: Block 1

Start of Block: Consent

Q2.1 The following statements are to ensure we have your consent and that you understand that your responses will be kept confidential and used anonymously

	Yes (1)	No (2)
I understand that my responses will be kept confidential (1)	○	○
I give my consent to use my feedback anonymously in this research report (2)	○	○
The information that I provide may be used anonymously after this project, for academic purposes by other researchers, subject to their own ethic clearance being obtained (5)	○	○

End of Block: Consent

Start of Block: General Questions

Q3.1 The following questions are purely for statistical purposes.

Q3.2 To which gender identity do you most identify?

- Female (1)
- Male (2)
- Other (3)

Q3.3 Please indicate your age group

- 18 - 29 (1)
- 30 - 39 (2)
- 40 - 49 (3)
- 50+ (4)

Q3.4 Please indicate your race

- African (1)
- White (2)
- Coloured (3)
- Asian (4)
- Other (5)

Q3.5 What is your highest level of education?

- No Matric (1)
- Matric (2)
- Certificate (3)
- Diploma (4)
- Bachelor's Degree (5)
- Honour's Degree (6)
- Master's Degree (7)
- Doctorate (8)
- Other (9)

Q3.6 How long have you been employed at your current company?

- Less than 1 year (1)
- 1 to 2 years (2)
- 2 to 5 years (3)
- 5 to 10 years (4)
- 10+ years (5)

Q3.7 In total, including all employment, how many years have you been in a decision-making role?

- Less than 1 year (1)
- 1 to 2 years (2)
- 2 to 5 years (3)
- 5 to 10 years (4)
- 10 to 20 years (5)
- 20+ years (6)

End of Block: General Questions

Start of Block: Research Questions

Q4.1 The following questions use a 7-point scale from strongly agree to strongly disagree.
Please select the option that closely represents your view on the statements that follow:

	Strongly agree (7)	Agree (6)	Somewhat agree (5)	Neither agree nor disagree (4)	Somewhat disagree (3)	Disagree (2)	Strongly disagree (1)
1. My current role requires me to make decisions (Q4.1_1)	○	○	○	○	○	○	○
2. I make decisions on a daily basis (Q4.1_2)	○	○	○	○	○	○	○
3. The decisions that I make are important to the performance of the organisation (Q4.1_3)	○	○	○	○	○	○	○
4. I need additional training to interpret the data and analysis available to me (Q4.1_4)	○	○	○	○	○	○	○
5. I am comfortable using the tools and technology required to understand the data available in the organisation (Q4.1_5)	○	○	○	○	○	○	○
6. Data visualisations make it easier and quicker to understand and make decisions (Q4.1_6)	○	○	○	○	○	○	○
7. I trust my gut and instinct to make decisions (Q4.1_7)	○	○	○	○	○	○	○

8. I see the value in data-driven decision-making (Q4.1_8)	○	○	○	○	○	○	○
9. I always refer to data analysed and visualised via dashboarding, reporting, deep dive analysis to make decisions? (Q4.1_9)	○	○	○	○	○	○	○
10. I know what course of action to take without referring to the data or analytics (Q4.1_10)	○	○	○	○	○	○	○
11. Looking at the data is an unnecessary step in my decision making process (Q4.1_11)	○	○	○	○	○	○	○
12. The information available in my organisation is sufficient for me to make the decisions that I need to make (Q4.1_12)	○	○	○	○	○	○	○
13. I have access to all the data that I need to make decisions (Q4.1_13)	○	○	○	○	○	○	○
14. The information that I need to use to make decisions is always timely (Q4.1_14)	○	○	○	○	○	○	○

15. I never struggle to find the data that I need to make decisions (Q4.1_15)	○	○	○	○	○	○	○
16. The data that I need is always correct (Q4.1_16)	○	○	○	○	○	○	○
17. It is easy for me to access the data that I need to make decisions (Q4.1_17)	○	○	○	○	○	○	○
18. The data that I use to make decisions is understandable (Q4.1_18)	○	○	○	○	○	○	○
19. I have the required skills to interpret the analysis provided to me to make decisions (Q4.1_19)	○	○	○	○	○	○	○
20. I use advanced analytic techniques to understand our business (Q4.1_20)	○	○	○	○	○	○	○
21. I find it easy to comprehend the data made available to me (Q4.1_21)	○	○	○	○	○	○	○

End of Block: Research Questions

9 Appendix B: Consent Form



Interview Consent Form

Research Title

The title of this study is: The use of data and analytics in strategic decision-making in a South African Pay-TV company.

Q2.1 The following statements are to ensure we have your consent and that you understand that your responses will be kept confidential and used anonymously

	Yes (1)	No (2)
I understand that my responses will be kept confidential (1)	○	○
I give my consent to use my feedback anonymously in this research report (2)	○	○
The information that I provide may be used anonymously after this project, for academic purposes by other researchers, subject to their own ethic clearance being obtained (5)	○	○

10 Appendix C: Participant Sheet

PARTICIPANT SHEET

To Morne Bosch-Serfontein
Chief Data Officer
South African Pay-TV company City
144 Bram Fischer Drive
Ferndale
Randburg
South Africa

Dear Mr. Bosch-Serfontein
My name is Prebashni Reddy. I am an MBA student at Wits Business School. As part of my studies, I am doing a research study entitled 'The use of data and analytics in strategic decision-making in a South African Pay-TV'.
The aim of the study is to understand if data is being used by senior management to make data-driven decisions.

As part of my MBA Research Report, different people will be interviewed ranging from senior managers who need to make strategic decisions to find out how they are currently making their decisions and to understand what the gaps are that could help in their decision-making. Understanding other challenges, if any, that stand in their way of creating a data-driven culture.
I would like to recognise the experts and people who contribute to this research and acknowledge them in my report. By agreeing to participate I recognise you as part of the contributing experts. However, if you disagree with this, I will not compel you. Your participation in this interview is voluntary, confidential and will be treated with anonymity. The interview will be done online in order to comply with the current covid-19 regulations of social distancing.

I would therefore appreciate your written consent if you are willing to participate in the study. There are no benefits, financially or otherwise to be gained from participation.
If you have any questions during or afterwards about this research, feel free to contact me or my supervisors on the details listed below. This study will be written up as a research report which will be available online through the university library website if you wish to receive a summary of this report. The data collected from this research project will be stored in the Witswaterand University archives. With your permission, the data collected from this research project may be used by other researchers (optional).

If you have any concerns or complaints regarding the ethical procedures of this study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrec-medical.researchoffice@wits.ac.za.

Thank you for taking time to read through this letter.
Yours Faithfully



_____
Prebashni Reddy
Cell Number: 082 040 0143 Email Address: prebash@mweb.co.za
Or
Supervisors
Thandiwe Chidzungu Cell: 0744351520 Email: 1312738@students.wits.ac.za

11 Appendix D: Permission Letter

29 October 2020

Wits Business School
2 St. David's Place
St. Andrews Road
Parktown
Johanneburg
2193

RE: AUTHORISATION TO CONDUCT RESEARCH

This letter serves to confirm that Prebashni Reddy, identity number 7509070128080, has been granted permission to conduct research on the Multichoice Group for her research project for the qualification of Masters of Business Administration (MBA) at Wits Business School.

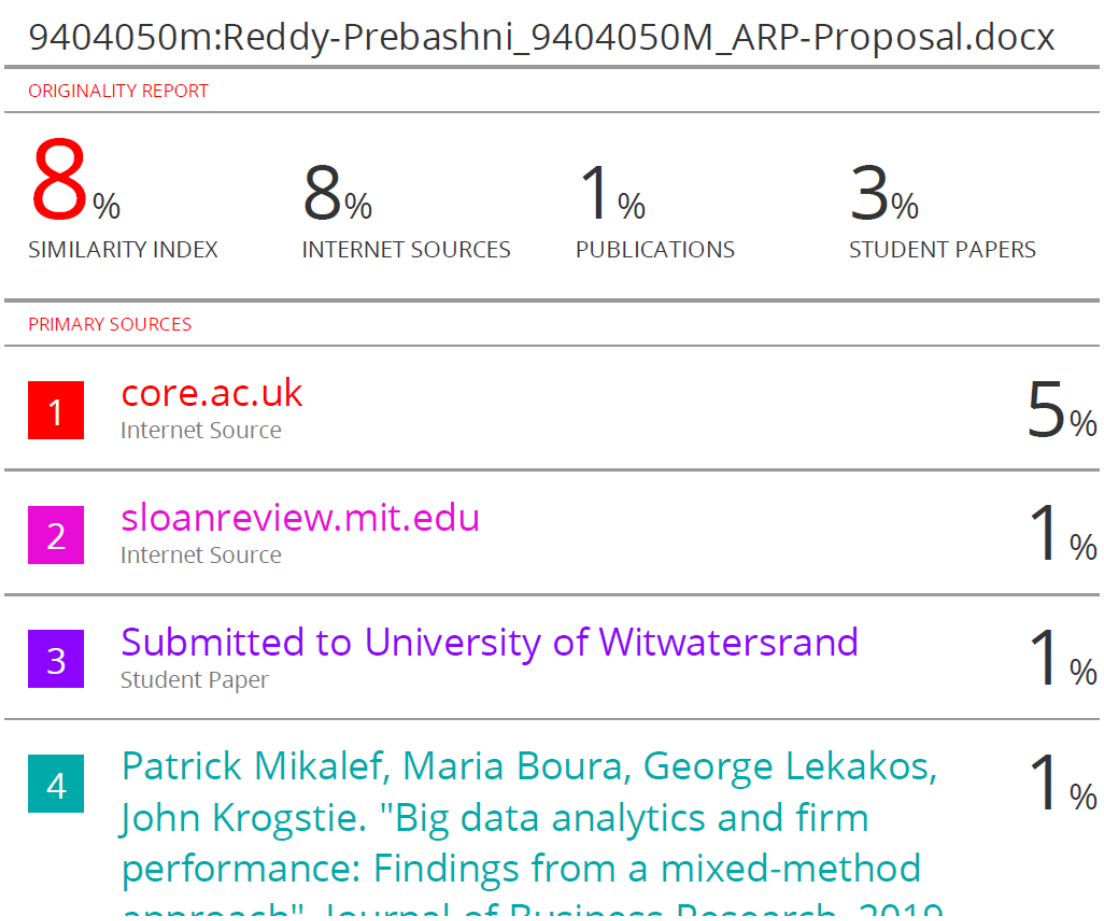
The title of the research is: **Evaluating the use of data analytics in strategic decision-making in a South African Pay TV company.**

Yours Sincerely



Morne Bosch-Serfontein
Chief Data Officer
Multichoice Centre

12 Appendix E: Turnitin Report



9404050m:Reddy-Prebashni_9404050M_ARP-Proposal.docx

ORIGINALITY REPORT

8%	8%	1%	3%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	core.ac.uk Internet Source	5%
2	sloanreview.mit.edu Internet Source	1%
3	Submitted to University of Witwatersrand Student Paper	1%
4	Patrick Mikalef, Maria Boura, George Lekakos, John Krogstie. "Big data analytics and firm performance: Findings from a mixed-method approach", Journal of Business Research, 2019	1%

13 Appendix F: Plagiarism Declaration



THIS DECLARATION IS TO BE ATTACHED TO ALL ASSIGNMENTS	
INDIVIDUAL ASSIGNMENT	
Student details	
Student Number/s: 9404050M	**Student name:** PREBASHNI REDDY
Email address: prebash@mweb.co.za	
Assignment details	
Course Code: BUSA 7417A	**Course Name:** APPLIED RESEARCH PROJECT
Assignment no. 1	**Due date:** 30 NOVEMBER 2020

Student Declaration

I am aware that plagiarism (the use of someone else's work without their permission and/or without adequately acknowledging the original source) is wrong and is a violation of both the General Rules for Student Conduct and the Plagiarism Policy of the University of the Witwatersrand.

I am aware that it is wrong and is a violation of both the General Rules for Student Conduct and the rules of the Wits Business School for a student to submit for a course, unit, or programme of study, without the written approval of the course instructor or the programme director, all or a substantial portion of any work for which credit has previously been obtained by the student or which has been or is being submitted by the student in another course, unit, or programme of study in the University or elsewhere.

I confirm that this assignment my own unaided work except where I have explicitly indicated otherwise.

I confirm that this assignment has not been nor will be submitted in whole or in substantial part in another course, unit, or programme of study in the University or elsewhere without the written approval of the course or unit instructor or the programme coordinator.

I confirm that I have followed the required conventions in referencing the words and ideas of others in this assignment.

I confirm that I understand that this assignment may at any time be submitted to an electronic plagiarism detection system, and may be stored electronically for that purpose.

I confirm that I have received a copy of the University's Plagiarism Policy S2003/351B and a copy of the General Rules for Student Conduct and Code of Conduct C2010/27.

I confirm that I understand that any and all applicable policies, procedures, and rules of the University and of the School may be applied if there is a belief that this assignment is not my own new and unaided work, or that have failed to follow the required conventions in referencing the words and ideas of others, and I understand that application of the policies, procedures, and rules may lead to the University taking disciplinary action against me.

Note: The attachment of this statement on any electronically submitted assignments will be deemed to have the same authority as a signed statement.

Student Signature: signed electronically	**Date:** 30 November 2020

14 Appendix G: Ethics Clearance Certificate

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/BA9404050M/752
This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	The use of data analytics in strategic decision-making in a South African Pay TV company
Investigator / Researcher	Miss Prebashni Reddy
Nature of Project	MBA (Research Article)
Decision of the Committee	Approved unconditionally
Issue Date of Certificate	2021-03-03
Expiry date	Date of submission of the project report
Chairperson	Prof Anthony Stacey ☎ +27 11 717 3587 +27 82 880 4531 anthony.stacey@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

06/03/2021
Date: